ESSAYS ON THE EFFECTS OF MONETARY POLICY ON FINANCIAL MARKETS

by

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Abstract

It is widely accepted that monetary policy exerts a powerful influence on financial markets. In this dissertation, I use micro level data to study the effects of unanticipated monetary policy decisions on stock returns, credit spreads, and firm investment. By focusing on the unanticipated component, I am able to estimate the causal effects on financial market variables and by using micro level data, I explore how firm heterogeneities can give rise to different effects. The first two chapters of this dissertation studies the effect on bank stock returns and firm level credit spreads. The third chapter builds upon the second by studying how policy interacts with credit spreads to affect investment.

In the first chapter, I study the effects of monetary policy surprises on bank stock returns. Banks are unique because the effects of rising interest rates on their value is ambiguous. On the one hand, higher interest rates lower their stock price by discounting future cash flows more and on the other hand, raises its stock price through higher net-interest margins. I provide event-study evidence that a reversal effect occurred, where prior to the Financial Crisis, bank stock returns declined upon a tightening surprise and that during the zero-lower bound period, bank stock returns increased.

The second chapter assesses the impact of monetary policy surprises on firm level credit spreads. I estimate that a 100 basis point tightening surprise leads to a 30 basis point decline in credit spreads - a result that is in stark contrast to traditional theories of monetary contraction. I find that this decline is mostly driven by a component related to risk premia and not by expected default. I rationalize the negative relationship between tightening surprises and credit spreads by theories of preferred habitat which state that policy has a higher pass-through effect on safer bond yields rather than riskier ones.

In my third chapter, co-authored with Yoshio Nozawa, I study the investment channel of monetary policy by exploring differences in the cost of external financing. I find that a one standard deviation higher level of credit spread leads to a 2% decline in the investment sensitivity to monetary policy. This implies that safer firms increase their investment much more during expansionary policy. My results shed light on the role of credit costs in the transmission of monetary policy on investment.

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Dedication

This thesis is dedicated to my parents Tom and Huei Jung Yuan.

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Chapter 1

The Effects of Monetary Policy Shocks on Bank Stock Returns

1.1 Introduction

We know that under normal circumstances rising interest rates reduce stock returns. But, we do not know if this effect holds in a low and unchanging interest rate environment for all firms. One particular type of firm that is especially exposed to interest rate changes are banks. Banks, which are in the business of borrowing and lending, are directly affected by interest rates and provide a natural appartus for which to study stock return responses in both environments. While bank stock returns face the same negative effects of interest rate increases as other firms, their revenues from lending are positively affected by higher rates making the overall effect of tightening ambigious. Do bank stock returns react differently from other firms in response to monetary policy surprises before and during the zero lower bound?

This paper addresses the difficulty of assessing the impact of a rise in the policy rate on stock returns by using changes in market expectations of interest rates around Federal Reserve announcements. Commonly referred to as monetary policy shocks, this measure over a short interval ensures that it is driven purely by monetary policy news and is uncontaminated by other types of information that may occur throughout the day. More importantly, this approach disentangles the impact of policy response towards changes in stock returns which is an endogeneity issue that can plague event studies. Because futures contracts exist before and during the zero lower bound, I can measure these shocks and aligning them with stock returns over the same time interval, seamlessly evaluate its effect on bank stock returns in both periods.

Event study results show that there exists a reversal interest rate effect for banks, where their stock returns decline in response to tightening surprises prior to the zero lower bound and increase during it. Banks seem to uniquely benefit from a monetary policy surprise tightening during the low interest rate environment suggesting that rate hikes are perceived to be good news above and beyond the negative discount rate effect all firms face. More specifically, this traditional discount rate channel posits that higher interest rates reduce the present value of future cash flows which subsequently lowers stock prices. Banks, on the other hand, have an additional channel of interest income which increases along with interest rates. What then is driving the differential response to monetary policy shocks between banks and non-banks? What bank characteristics explain cross sectional differences in response to these shocks? I find that riskier banks, as defined by items on their balance sheet, face an amplified effect on their stock returns. In addition, I find that banks with a larger maturity mismatch between their assets and liabilities as well as those with greater market power over deposits face an attenuated effect on their returns. To make sense of these empirical results, I combine a standard banking model with features of market power over the deposit market to draw implications on how sensitivities should differ cross-sectionally. Furthermore, I turn to the literature of Campbell and Shiller (1988a) who show that stock return movements can be decomposed into news about cash flows, real rates, and expected returns in order to uncover what source of news is driving the monetary policy sensitivity.

Section 1.2 discusses relevant literature, Section 1.3 describes the data, Section 1.4 documents the event study results, Section 1.5 motivates the model, Section 1.6 empirically examines the source of news driving the results, and Section 1.7 concludes.

1.2 Related Literature

A number of papers have used event studies to analyze the effects of monetary policy on financial markets. The seminal work of Flannery and James (1984) found that bank stock returns move inversely with unanticipated interest rate changes and that this sensitivity is positively related to the size of the maturity difference between a bank's nominal assets and liabilities. The idea is that all else equal, unexpected inflation affects the value of nominal assets rather than real assets. Firms with fewer nominal assets relative to nominal liabilities will therefore benefit from unanticipated monetary policy and this effect is directly related to the term structure of its nominal position. This *maturity mismatch hypothesis* predicts that differences in the maturity composition of net nominal assets can explain differences in the interest rate sensitivity of bank stock returns. Aharony et al. (1986), Bae (1990), Kwan (1991), and Akella and Greenbaum (1992) all reach similar conclusions that interest rate sensitivities are highly correlated with the maturity structure of financial institutions. However, all of these papers proxy monetary policy in a similar way by simply computing the difference in interest rates over an event period. Therefore, interpreting their reported sensitivities raise endogeneity concerns because their assumption of exogenous monetary policy is questionable.

The issue of endogeneity and finding a reasonably exogenous measure of monetary policy is inherently difficult when one uses changes in the short term interest rate because of the Federal Reserve's reaction to developments in the macroeconomy [1]. For example, how can we isolate interest rate changes that are exogenous from rate changes due to broader economic conditions? This issue was first addressed by Kuttner (2001) who separated changes in the federal funds rate target into an an-

[1] Rigobon and Sack (2003) identifies monetary policy based on the heteroskedasticity of stock market returns and Wright (2012) uses heteroskedasticity of monetary policy shocks to measure its effect on long-term interest rates.

ticipated and an unanticipated component around Federal Open Market Committee announcements. By replacing interest rate changes of the aforementioned studies with a "surprise" targets fund rate change, they are better able to capture exogenous movements in policy and define them as monetary policy shocks [2]. Following Kuttner (2001)'s methodology, a voluminous literature on using monetary policy surprises emerged. Bernanke and Kuttner (2005) studied the impact of monetary policy on equity prices by focusing on days in which the Federal Open Market Committee (FOMC) decided to change the target federal funds rate and found that on average, an unanticipated 25-basis-point cut in the target rate is associated with a 1% increase in value weighted stock returns. In addition, they take a more structured approach to disentangle these stock return movements into the contributions of expected future dividends (cash flows), future expected real interest rates used to discount them, and equity premiums that come from holding stocks. They find that most of the stock returns reaction occurs through expected future dividends and the equity premium. Following the same spirit of focusing on FOMC meetings, Gurkaynak et al. (2004) applied an intraday event-study to show that monetary policy is captured not only by the current federal funds rate "target factor", but also a factor associated with the "future path of policy". They find that the path factor has a greater effect on the long end of the yield curve but only a small effect on the stock market. Subsequent literature on understanding the effects of monetary policy shocks have largely

[2] FOMC announcements of target rate changes began in February 1994. Prior to that, the market inferred its target based on the Fed's behavior through open market operations

followed in the footsteps of Kuttner (2001) and Gurkaynak et al. (2004) and have motivated structural models using these reduced form results [3].

A more related work by English et al. (2018a) re-examines the relationship between interest rate sensitivity and maturity mismatch by estimating the reaction of intraday bank stock returns induced by monetary policy announcements. In line with the literature, they first find that bank stock prices decline following an unanticipated increase in the level and slope of interest rates. By utilyzing bank balance sheet information on maturities of their assets and liabilities, they conclude that banks heavily engaged in maturity transformation face a smaller decline in their stock price following a surprise steepening of the yield curve. This result is in line with the conventional structure of banks as maturity transformers who benefit from a steep yield curve. While this study and others that have preceeded it allow us to study the net effects of monetary policy surprises on the financial health of a bank, we are unable to guage whether the institution is increasing its risk and adjusting its portfolio. The underlying changes that we see from stock price changes reveal nothing about the choices that financial institutions make to adjust its risk profile [4].

More recently, Chodorow-Reich (2014) studies the effect of unconventional monetary policy during the winter of 2008-2009 on banks and life-insurance companies. These unconventional policies included lowering the federal funds target rate to zero,

[3] For example, Ottonello and Winberry (2018) uses these monetary policy shocks to find that firms with low leverage and high credit ratings are more responsive to monetary policy

[4] One approach by Begenau et al. (2015) finds that banks do not completely hedge their duration risk from its portfolio.

purchases of Treasury and mortgage-backed securities and other agency securities, and forward guidance on the future path of the target rate. Using high-frequency event studies of the impact on credit default swaps, yields, and stock prices of banks around unanticipated FOMC announcements, Chodorow-Reich (2014) finds a strong and stabalizing impact on banks and life-insurance companies. In particular, he finds that CDS premiums fell and stock prices rose following the introduction of unconventional monetary policy.

My paper adds to the literature by comparing the period prior to the Financial Crisis with the period during the zero lower bound and how monetary policy announcements affected banks differently. The recent low interest environment has garnered additional interest as banks begin to slowly adjust towards policy normalization. Moreover, media attention has focused over the recent period, on how low interest rate environments affect bank health and profitability, with a fairly divisive conclusion [5]. A recent working paper by Wang et al. (2018) separates the effects of changes in the two-year Treasury yield on bank stock returns between low and high interest rates environments. They find a similar reversal effect where bank returns increase in a low interest rate environment. In addition to documenting the reversal effect on bank returns, this paper also asks whether different balance sheet characteristics affect this sensitivity.

[5] WSJ (2018): "Low Interest Rates Don't Hurt Bank Profits" and St. Louis Fed (2016): "Are Banks More Profitable When Interest Rates Are High or Low?"

1.3 Data

1.3.1 Banks

Nearly all work studying individual banks require using the quarterly Consolidated Reports of Condition and Income (Call Report) filed to the Federal Deposit Insurance Corporation (FDIC). All commercial banks in the United States are required to file the FFIEC 031 and FFIEC 041 forms, where data can be obtained directly from the FDIC. Bank holding companies are required to submit the FR Y-9C form which can be accessed from the Federal Reserve Bank of Chicago database. The FR Y-9C form is prepared by banks that have at least $500 million worth of assets. Bank holding companies (BHC) typically own commercial banks and can themselves also be owned by another holding company. I focus on bank-holding companies, which are publicly traded and therefore, have an associated stock return. Some crucial bank information such as the maturity structure of assets and liabilties, however, are only available at the bank subsidiary level and I aggregate them to the holding company level.

In the baseline event study, I estimate regressions of intradaily stock returns for both banks and nonbanks on monetary policy surprises (defined below). This information comes from the NYSE Trade and Quote (TAQ) database which provides millisecond intraday transactions data for all securities listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and the NASDAQ National Market System (NMS) starting in 1993. I calculate the price at a particular time by taking the average of the recorded bid and ask prices and compute the one-hour return around an FOMC meeting as follows [6] :

$$R_{i,t} = \frac{P_{14:45:00}}{P_{13:45:00}} \tag{1.1}$$

where P_t is the price of the security at time t.

My subsequent analysis requires a larger sample of banks than those listed in TAQ and which have available balance sheet information. While I'm unable to recover high-frequency intraday prices from other institutions, I gather daily and monthly stock price information for other banks from The Center for Research in Security Prices (CRSP). Using a link-table provided by the Federal Reserve Bank of New York, I am able to match these banks with their corresponding Call Report indentifier (RSSD) [7]. With each bank from CRSP having an associated RSSD identifier, I can easily match stock returns with balance sheet information. This is also matched with data from Compustat which provides financial and market information such as book and equity value on all global firms.

[6] The choice of using a one-hour window follows that of Gurkaynak et al. (2004) and English et al. (2018a) and allows time for price-discover by the market to occur. Using a wider window may introduce news other than monetary policy

[7] `https://www.newyorkfed.org/research/banking_research/datasets.html`

1.3.2 Monetary Policy Shocks

Monetary policy surprises are measured as intradaily changes of various interest rate futures contracts around a one-hour window of FOMC announcements [8]. This narrow window period is chosen in order to avoid contamination from other sources of information besides monetary policy. More importantly, this approach disentangles the impact of policy response towards changes in economic developments which is an endogeneity issue that can affect event study estimates. Positive values of these shocks are interpreted as surprise tightenings and negative values as surprise easings [9]. Federal Open Market Committee meetings typically occur eight times a year and announcements are released at approximately 2:15 PM (Eastern Standard Time). It is important to note that in February 1994, the FOMC began this practice of issuing post meeting announcements and most of my sample captures the one hour window around this. However, shocks also existed prior to 1994 and the market received information of policy stances by interpreting the size and type of open market operations. I consider FOMC meetings from February 1st, 1984 to April 27th, 2016 which is a total of 317 meetings [10]. All other interest rate variables come from the FRED and Bloomberg database.

[8] I thank Jonathan Wright and Eric Swanson for providing me with this data set

[9] A notable surprise easing occurred on March 18, 2009 when the Federal Reserve announced an additional purchase of $ 750 billion of agency mortgage-backed securities. As a result, the 10-Year Treasury fell 40 basis points within the hour

[10] There has, however, been intermeeting policy moves where announcements occurred unscheduled and did not necessarily occur at 2:15PM. These include October 15, 1998; January 3, 2001; and April 18, 2001

1.4 Event Study Results

1.4.1 Time Series

1.4.1.1 All Firms

In order to test whether my sample is reflective of the literature, I begin by examining whether my event study results on the aggregate stock market are in line with what previous authors have found. Among the futures contracts available, I measure monetary policy shocks as the surprise in federal funds rate futures contract in the current month scaled by the number of days in the month and denote this by $MP1$[11]. Given the presence of unconventional monetary policy, I split the sample into two periods: the pre-zero lower bound (pre-ZLB) period (February 4, 1993 - December 16, 2008) and the zero lower bound (ZLB) period (January 28, 2009 - April 4, 2016). While $MP1$ is appropriate during the pre-ZLB period, there were no surprise changes in the target funds rate during the ZLB period. Therefore, during the ZLB, I use the surprise changes in the fourth eurodollars futures contract $ED4$ which measures the market's expectation on what the LIBOR rate will be in a year. This variable has been described by Gurkaynak et al. (2004) as an appropriate indicator for the path of future policy and in fact, during the onset of the Financial Crisis (2009), the market priced $ED4$ as if lift-off would occur in the next six months. I also

[11] This measure is also used by Kuttner (2001), Gurkaynak et al. (2004), and Bernanke and Kuttner (2005)

consider the residuals from the projection of changes in the fourth eurodollar futures contract $ED4_t$ onto the target surprise $MP1_t$. These residuals, $PATH_t$ represent all aspects of FOMC announcements that move futures rate for the upcoming year *without changing* the current federal funds rate.

On the firm side, I remove companies that have fewer than 30 observations of intradaily returns on FOMC days and remove the September 17, 2001 meeting which followed the terrorist attacks[12]. Taking an average across all firms, I compute an aggregate time series of intradaily return and run the following time series regression:

$$\bar{R}_t = \begin{cases} \beta_0 + \beta_1 MP1_t + \beta_2 Path_t + \epsilon_t & t \in \text{pre-ZLB} \\ \beta_0 + \beta_1 ED4_t + \epsilon_t & t \in \text{ZLB} \end{cases} \tag{1.2}$$

where $\bar{R}_t$ is the average across all intradaily returns of all firms in the NASDAQ on FOMC meeting t.

[12] The FOMC had an unscheduled meeting on September 17, 2001 to cut interest rates by 50 basis points

	(1) February 1993 - December 2008	(2) January 2009 - December 2014
MP1	-0.0227*	
	(0.0120)	
PATH	-0.0250**	
	(0.0106)	
ED4		-0.0701*
		(0.0389)
R^2	0.109	0.140
N	139	48

Table 1.1: The Response of Average Stock Returns (NASDAQ) to Monetary Policy Shocks

The table reports the results of a regression of average intradaily returns on FOMC meeting t for both the period before the zero lower bound and during it. Prior to the zero-lower bound, returns on FOMC meeting t are regressed on the surprise component of the change in the federal funds target (MP1) and on the PATH factor. The PATH factor is the residual from a regression of ED4 on MP1. There are 7,291 firms included in the sample. All variables are expressed in decimal form and are interpreted as the response of stock returns to a surprise of a 1% point surprise rise. Column (1) corresponds to the period prior to the zero-lower bound and Column (2) includes the zero-lower bound. Heteroskedasticity-consistent standard errors reported in parenthesis

Table 1.1 reports the results of the time-series regression. Prior to the zero-lower bound, a 1% surprise increase in the target rate is associated with a 2.27% decline in the average stock market. This value is closely aligned with Bernanke and Kuttner (2005) and Gurkaynak et al. (2004) who find a value of 5% and 4% respectively. The path surprise leads to a statistically significant decline of 2.5% decline in the aggregate stock market [13]. Using the fourth eurodollar futures contract drastically increases the sensititivity to 7%. Given that there is limited literature that has focused exclusively

[13] Gurkaynak et al. (2004) finds an insignificant effect of the path surprise on the S&P 500 which could be due to the different sample of firms used and time period of 1991-2004

on the effects of these shocks during the zero lower bound, this magnitude is difficult to compare. One exception is Ampudia and Van den Heuvel (2017) who find that a 100bp increase in the Euro OverNight Index (EONIA) corresponds to an 8% increase in European bank stock returns during crisis periods with low interest rates.

	Rigobon and Sack (2003)	Ehrmann and Fratzscher (2004)	Bernanke and Kuttner (2005)	Gurkaynak et al. (2004)	Yuan (2019)
Identification	Heteroskedasticity	Survey	Futures	Futures	Futures
Data	SP500	SP500	CRSP-weighted	SP500	NASDAQ
β_1	-6.2%	-5.5%	-5.3%	-4.03%	-2.27%

Table 1.2: Comparisons with the Literature

The table reports the identification methodology for monetary policy surprises, the data-set considered, and the sensitivity of equity returns to these surprises. All β_1 coefficients are negative and correspond to a 1% surprise tightening.

In Table 1.2, I compare my return sensitivity during the pre-ZLB period with the literature to determine whether the surprises generated sensible results in my sample of firms. My estimate is smaller than what previous authors have documented which can be attributed to them studying the aggregate S&P 500 which comprises different firms. All of the aforementioned papers also focus on daily returns around announcements which could contain news other than monetary policy. If this is the case, they are overestimating their coefficients because of returns being potentially driven by other variables.

1.4.1.2 Banks

There are large heterogeneities across banks in my sample which affect its time series aggregation sensitivities. For example, riskiness, leverage, and its overall size make the banks in my sample vastly different from one another. In order to test whether there are significant differences between the sensitivity of bank stock returns and all other returns, I run industry-by-industry time series regressions using returns from daily industry portfolios from Kenneth French's website. The portfolio is constructed as follows: each NYSE, AMEX, and NASDAQ stock is assigned to an industry portfolio at the end of June of year t based on its 4 digit SIC code at the time. Returns are then computed from July of t to June of $t+1$. I estimate for each of the 49 industries, the same time series regression as given by Equation 1.2. For each of the industry portfolios, there is a statistically significant decline in daily returns following a monetary tightening shock during the pre-ZLB period. Figure 1.1 plots the estimated coefficient for each of the 49 Industry portfolios before (green bar) and during (red bar) the zero-lower bound. It is clear that for the period prior to the zero lower bound, a monetary policy tightening surprise led to a negative effect on stock returns. When turning over the zero lower bound sample, all industries continue to face a negative coefficient except for Banks. In particular, in the pre-ZLB period, a 1% surprise increase in the fourth eurodollars futures contract led to a decline of 6% in bank stock returns. During the ZLB period, however, this same affect led to an increase of 2% in bank stock returns which suggests a reversal effect that exists in the time series. I now turn to cross-sectional evidence using my data of intradaily returns to examine whether banks and non-banks faced different sensitivities to monetary policy surprises and whether this reversal effect exists.

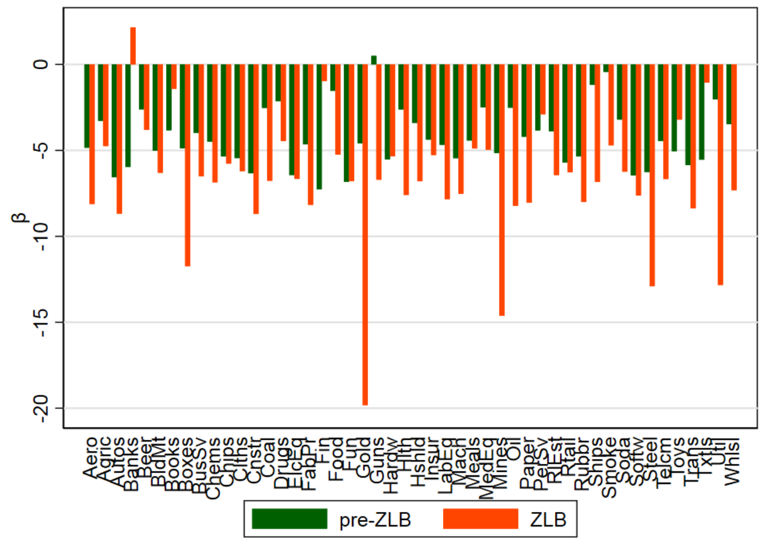


Figure 1.1: Regression Coefficients From French 49 Portfolio Daily Return

This bar graph shows the estimated β coefficient on ED4 for each of the 49 Industries using Kenneth French's data library. The green line bar corresponds to the sample period prior to the ZLB and the orange bar corresponds to the same period during the ZLB

1.4.2 Pooled Regression

I now consider the universe of firms for which I have intradaily data from TAQ and separate them into banks (b) and nonbanks (nb). Banks are defined as institutions that have an RSSD ID which is a unique identifier assigned by the Federal Reserve. Again, I split the sample time period to account for differences between the pre-ZLB with the ZLB. For the two groups, I run the following pooled regression (over the cross-section and time series) with standard errors clustered at the FOMC date level:

$$R_{i,t} = \beta_0 + \beta_1 MPS_t + \epsilon_{i,t} \tag{1.3}$$

where $R_{i,t}$ is the intradaily return of firm i and MPS_t is the intradaily monetary policy surprise. Similar to the aggregate time series results in Table 1.1, I define the monetary policy surprise MPS_t as the surprise component of the change in the federal funds target (MP1) and the $PATH$ factor prior the zero lower bound and changes in the fourth eurodollar futures contract (ED4) during the zero lower bound. Table 1.3a shows the estimation results for non-banks. For non-banks, prior to the zero lower bound, a 1% surprise tightening in the path factor leads to a 2.27% decline in returns and a 2.54% decline during the ZLB. This is quite similar to the aggregate time series results of Table 1.1 which is unsurprising given that most of the sample are non-banks. Clustering standard errors at the FOMC announcement date level allows for correlation among firm stock returns within a meeting but independent across meetings. The results for banks is presented in Table 1.3b and shows the existence of the reversal effect that we see from Figure 1.1. Prior the zero lower bound, bank stock returns behaved quite similarly to non-banks with a 1% surprise tightening leading to a 1.8% drop in returns. During the zero-lower bound, however, this sensitivity reversed signs and became a 1.20% increase.

As a robustness check, I re-estimate the cross-sectional regression using monthly returns from CRSP and find a similar reversal from negative 96 bp to positive 165bp. The results presented thus far assume that bank stock returns are impacted only by monetary policy surprises during the FOMC event window considered.

(a) Pooled Regression of Non-Bank Stock Returns on Monetary Policy Shocks

	(1) February 1993 - December 2008	(2) January 2009 - December 2014
MP1	-0.00864	
	(0.00722)	
PATH	-0.0227***	
	(0.00806)	
ED4		-0.0254
		(0.0335)
R^2	0.022	0.006
N	330054	150938

(b) Pooled Regression of Bank Stock Returns on Monetary Policy Shocks

	(1) February 1993 - December 2008	(2) January 2009 - December 2014
MP1	-0.00827	
	(0.00531)	
PATH	-0.0176***	
	(0.00524)	
ED4		0.0191***
		(0.00460)
R^2	0.030	0.070
N	8033	2764

Table 1.3: Pooled Event Study Regressions

This table reports the results of estimating Equation 1.3, a pooled regression (over the cross-section and time series) of non-bank (Panel 1.3a) and bank (Panel 1.3b) intradaily returns $R_{i,t}$ on FOMC meeting dates for both the period before the zero lower bound and during it. Prior to the zero-lower bound, returns on FOMC meeting t are regressed on the surprise component of the change in the federal funds target (MP1) and on the PATH factor. The PATH factor is the residual from a regression of ED4 on MP1. There are 5,803 non banks included in the sample. All variables are expressed in decimal form and are interpreted as the response of stock returns to a surprise of a 1% point surprise rise. Column (1) corresponds to the period prior to the zero-lower bound and Column (2) includes the zero-lower bound. Returns are winsorized at the 2% and 98% level. Standard errors are clustered at the FOMC date level

However, interest rates fluctuate daily and it is important to address whether these normal movements also affect bank stock returns in the same way suggested by these event study results. In other words, are the effects on bank stock returns purely based on interest rate changes or on FOMC induced interest rate surprises? I show in Appendix A.5 that FOMC days are indeed unique and produce different sensitivities on bank stock returns. For example, I show that regressing bank stock returns on changes in various Treasury yields display a reversal effect only on FOMC meeting days (Table A.1) but not on all other non-FOMC days (Table A.2) suggesting a unique effect on announcement days. Furthermore, I show that during the pre-ZLB period (Table A.4), a 1% increase in the 2-Year Treasury yield had a 5.5% larger negative effect on FOMC days relative to non-FOMC days. This could occur perhaps because on non-FOMC days, the positive effect of yields on bank stock returns is due in large part to a macroeconomic effect where a stronger economy is associated with higher yields and returns. The relationship on FOMC days, however, could better capture unanticipated shifts in policy. Finally, in Appendix A.6, I show that the reversal of bank returns also exists when I estimate the event study and identify shocks by heteroskedasticity, which assumes that the variance of monetary policy shocks is greater on FOMC days vs non-FOMC days.

While these results are informative of the change in direction of bank return sensitivities, they do not explain what characteristics of banks could impact its magnitude. In the next section, I describe a model to motivate why a bank's maturity mismatch, riskiness, and market power could have a differential impact on a bank's sensitivity to monetary policy shocks. Finally, I use these three characteristics and ask which component of news (cash flows, discount rate, or expected returns) is driving these responses.

1.5 Model

1.5.1 Motivation

Motivated by the reversal effect that I find empirically for bank stock returns, I consider a model that can account for this as well as bank characteristics that should show stronger or weaker sensitivities to monetary policy. There has been an emerging literature that explores the prolonged effects of remaining at the zero lower bound. Also known as a "liquidity trap", standard New Keynesian models predict that the economy enters into a deep recession where consumption and growth can be stimulated by forward guidance and promises to keep interest rates low in the future. Moreover, these models suggest that growth is bad and that the destruction of output, capital, and productivity can raise GDP (Cochrane (2013). These results seem to suggest that the laws of economics flip signs during prolonged periods of low interest rates. I consider a model in which the same reversal occurs for bank stock returns during the zero lower bound period.

Brunnermeier and Koby (2018) has argued that the bank lending channel reverses during this period and that a lower policy rate can become contractionary. This occurs because the recapitalization gains from accomodative policy are offset by decreases in the bank's net interest margin. More specifically, banks with long term fixed assets benefit from a surprise rate cut because they continue to receive high interest payments and can refinance it at a lower rate. This increases the value of the bank's equity which relaxes any regulatory constraints they face. However, the lower policy rate also contracts the bank's net interest margin. Under the case of a perfectly competitive financial market, a lower policy rate will pass through to both loan and deposit rates leaving the net interest margin unaffected. Therefore, banks unambigiously benefit from an accomodative policy surprise. This implication will change when we consider the more realistic fact that banks have market power and do not perfectly adjust deposit rates for their customers. During normal times, any tightening surprises will induce capital losses on banks but also lead to higher net interest margins. If the former effect is greater than the latter, banks will face an overall decrease in their net worth leading to tighter capital constraints and a reduction in its stock return. However, if the effects on higher net interest margin surpasses its capital losses, this will lead to an increase in overall net worth, loosening capital constraints and increasing the bank's stock return. Brunnermeier and Koby (2018) defines the point at which this occurs as the "reversal interest rate". My empirical results test the implications of this theory and how this mechanism is affected by a bank's maturity mismatch, risk, and market power.

1.5.2 Set-Up

I consider a partial equilibrium banking model similar to that of Brunnermeier and Koby (2018). In the model, banks choose an interest rate to charge on loans i^L, an interest to pay on deposits i^D, and a quantity S of safe assets to hold. Banks have some market power and can mark-up i^L and mark down i^D. Banks also have an equity endowment E which represent their portfolio of long term asset holdings.

1.5.2.1 Banks

Assets

Banks issue loans L according to some loan demand function $L(i^L)$, where $L^{'} < 0$. A higher loan rate is associated with more expensive cost of investment and thus leads to a lower demand for loans. In this partial equilibrium setting, loans are only a function of the nominal loan rate that the bank chooses i^L. We can think of these loans as standard consumer, credit card, and commercial loans. Banks can also choose to invest in some quantity of safe asset S which are available in a perfectly elastic supply. These safe assets can include bonds, reserves, or cash and offer a return equal to the nominal interest rate i which is determined by the central bank's policy rate.

Liabilities

Banks use deposits D from households to fund their lending and investment activity. These deposits are determined by the deposit function $D(i^D)$, where $D^{'} > 0$. A higher deposit rate is attractive for households who wish to earn a higher return on their savings. I assume that households in this economy can shop around for better rates if the rate offered i^D is too low.

In addition, banks also have some initial book equity $E_0(i)$ which is a function of the nominal interest rate i. Banks can potentially acquire unexpected capital gains following an easing shock or capital losses following a tightening shock. This occurs because of the duration risk that banks face, where a lower policy rate induces capital gains on long term assets they hold. In addition, risky assets that banks hold will be discounted at a lower rate and thus increase the price of these securities leading to further capital gains. Therefore, $E_0^{'}(i) < 0$.

Capital and Risk Constraints

Banks face a regulatory constraint that limits how much risky loans they can issue. If we assume that ψ^L is some risk weight determined by regulators, then the amount of risky loans that can be issued must be covered by the bank's profit.

$$\psi^L L \leq \pi \tag{1.4}$$

Liquidity Constraints

Banks also face a liquidity constraint where its safe asset holdings S must cover a certain fraction of deposits ψ^D. This constraint reflects the fact that banks need to have a buffer of assets in the event of a sudden outflow of deposits and cash above and beyond what is covered by deposit insurance. It can also be interpreted as the recent Liquidity Coverage Ratio regulation where banks need to hold highly liquid assets S in order to meet short term liabilities D.

$$\psi^D D \leq S \tag{1.5}$$

If we interpret S as reserves, Equation 1.5 can also be thought of the bank's reserve requirement. The bank must keep a fraction ψ^D of deposits as reserves. Since I assume that banks do not earn interest on excess reserves, they will not hold excess reserve and Equation 1.5 holds with equality.

Bank's Problem

$$\begin{aligned}
\pi = \max_{S, i^L, i^D} \quad & (1+i^L)L + (1+i)S - (1+i^D)D \\
\text{subject to} \quad & L + S = D + E_0(i) \\
& \psi^L L \leq \pi \\
& \psi^D D \leq S \\
& 0 \leq i^D \\
& L = L(i^L) \\
& D = D(i^D)
\end{aligned} \tag{1.6}$$

where π is the maximized profits of the bank, i^L is the loan rate the bank chooses to charge, L is the loan demand function the bank faces, i is the nominal interest rate chosen by the central bank, S is the quantity of safe assets the bank chooses, i^D is the deposit rate the bank chooses to pay, and D is the deposit supply function the bank faces.

The solution to the bank's problem is:

$$i^{*L} = i + \underbrace{\frac{1}{\epsilon^L}}_{\text{mark-up}} + \underbrace{\frac{\lambda^L}{1+\lambda^L}\psi^L - \frac{\lambda^D}{1+\lambda^L}}_{\text{capital constraint}} \tag{1.7}$$

$$i^{*D} = \max\left(i - \underbrace{\frac{1}{\epsilon^D}}_{\text{mark-down}} + \underbrace{\frac{\lambda^D}{1+\lambda^L}(1-\psi^D)}_{\text{liquidity constraint}}, 0 \right) \tag{1.8}$$

where ϵ^f is the semi-elasticity of the function f with respect to the loan and deposit rates, λ^L and λ^D are the Lagrangian multiplier on the capital and liquidity constraint, respectively. From Equation 1.7, we can see that there is a mark-up relative to the nominal interest rate on rates that banks charge on loans and from Equation 1.8, a mark-down on deposit rates paid out. Equation 1.8 shows that the bank does not allow the deposit rate to fall below zero which is the zero lower bound constraint. When the capital and liquidity contraints are both slack, the multipliers λ^L and λ^D are simply zero.

In order to see the role that market power plays in determining deposit rates, suppose for simplicity, that liquidity and capital constraints are slack. We can then rewrite the optimal deposit rate as:

$$i^{*D} = i - \frac{1}{\epsilon^D} \tag{1.9}$$

where $\frac{1}{\epsilon_D}$ is the mark-down that banks charge over the deposit rate. Define the spread that bank i charges its depositers as follows:

$$s_i \equiv i - i^D \tag{1.10}$$

Intuitively, the larger the spread s_i is, the more bank i is able to extract from depositors in order to earn more profit. The spread s_i is determined in equilibrium by the amount of deposits that households demand. I now turn to the household's problem of choosing deposits.

1.5.2.2 Households

The representative household is modeled similar to Drechsler et al. (2017) where each maximizes utility over final wealth W and liquidity services l according to a constant elasticity of substitution aggregator:

$$u(W_0) = \max\left(W^{\frac{\rho-1}{\rho}} + \lambda l^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}} \tag{1.11}$$

where λ is a share parameter that describes the relative importance of liquidity over final wealth and ρ is the elasticity of substitution between wealth and liquidity services.

I assume that $\rho < 1$ which corresponds to wealth and liquidity being complements. Liquidity services l are also a composite of cash holdings M and deposits D according to a CES aggregator:

$$l(M, D) = \left(M^{\frac{\epsilon-1}{\epsilon}} + \delta D^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}} \tag{1.12}$$

where δ measures the liquidity of deposits relative to cash and ϵ is the elasticity of substitution between cash and deposits. Equation 1.12 captures the fact that both cash M and deposits D are used in transactions and contribute to liquidity needs and substitution between these types will determine the behavior of spreads. Like Drechsler et al. (2017) and Tella and Kurlat (2017), I assume that deposits and cash are substitutes and therefore $\epsilon > 1$. Because this model requires some differentiation between banks, I assume that deposits D are a composite good produced by a set of N banks.

$$D = \left(\frac{1}{N}\sum_{i=1}^{N} D_i^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}} \tag{1.13}$$

where $1 < \eta < \infty$ is the elasticity of substitution across banks. Deposits are imperfect substitutes which give banks market power over the spreads they charge s_i. It is convenient to introduce the weighted average deposit spread $s \equiv \frac{1}{N}\sum_{i=1}^{N}\frac{D_i}{D}s_i$ which weights by the amount of bank i's deposits over the total amount of deposits. The budget constraint of households is:

$$W = W_0(1+i) - Mi - Ds \tag{1.14}$$

where the final wealth W is equal to the return they earn on their initial wealth W_0 by investing in the nominal interest rate and the amount they forego from holding cash M. This expression is somewhat unconventional, as most banking models have depositors earning a deposit rate i^D. However, recall from Equation 1.10 that s is a spread and thus, accounts for the fact that depositors are paid a deposit rate i^D. Households choose the amount of deposits to leave at bank i, D_i by taking as given the mark-up or spread of the bank s_i subject to the constraint that aggregate deposits are formed as a composite good produced by a set of N banks.

Household's Problem

$$\begin{aligned} \min_{D_i} \quad & \sum_{i=1}^{N} D_i s_i \\ \text{subject to} \quad & D = \left(\frac{1}{N}\sum_{i=1}^{N} D_i^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}} \end{aligned} \tag{1.15}$$

Interpreting the weighted average deposit spread s as an overall cost of deposits D, we can show that in a symmetric equilbrium that the elasticity of demand for bank i's deposits is given by:

$$\frac{\partial D_i/D_i}{\partial s_i/s_i} = \frac{1}{N}\left(\frac{\partial D/D}{\partial s/s}\right) - \eta\left(1 - \frac{1}{N}\right) \tag{1.16}$$

Equation 1.16 shows that as bank i increases its spread s_i, it will face outflows from two sources: an aggregate effect and an inter-bank effect. By raising its spread s_i, this makes the overall spread s greater and results in deposits D being more expensive overall. This effect is especially large if banks are located in more concentrated areas with fewer competitors (low N). The second source occurs when the bank's spread s_i increases by one percent, the average spread will rise by $\frac{1}{N}$. Therfore, bank i's relative spread increases by 1-$\frac{1}{N}$ and outflows will occur at the rate η, the elasticity of substition across banks. Drechsler et al. (2017) assumes that the elasticity of demand for bank i's deposits is -1 and using this fact, we can arrive at the following expression for market power [14]:

$$-\frac{\partial D/D}{\partial s/s} = 1 - (\eta - 1)(N - 1) \equiv \mathcal{M} \tag{1.17}$$

The expression in Equation 1.17 is a quantity that can be interpreted as market power, as it is greater when there is fewer banks competing (low N) or because its deposits are less substitutable (low η). Our ultimate goal is to understand how bank stock returns respond to interactions between monetary policy shocks and measures of market power $\mathcal{M}$. In order to solve Equation 1.17 for s in closed form, I follow Drechsler et al. (2017) and assume that $\lambda \to 0$, which removes the impact of the cost of liquidity on total wealth. With this, we can represent the aggregate deposit elasticity as:

$$-\frac{\partial D/D}{\partial s/s} = \left[\frac{1}{1+\delta^{\epsilon}(\frac{i}{s})^{\epsilon-1}}\right]\epsilon + \left[\frac{\delta^{\epsilon}(\frac{i}{s})^{\epsilon-1}}{1+\delta^{\epsilon}(\frac{i}{s})^{\epsilon-1}}\right]\rho \tag{1.18}$$

[14]The proof for this derivation is provided in Appendix A.2

which shows that the household's elasticity of demand for deposits is a weighted average of their elasticity of substitution to cash ϵ and bonds ρ. It is worth noting that Equation 1.18 gives implications for the spread during high and low interest rate environments. Suppose that the nominal interest rate i is high. This makes cash a relatively expensive source of liquidity and any substitution that households make is towards bonds. The elasticity of demand $\frac{\partial D/D}{\partial s/s}$ is therefore close to ρ which is a small number less than 1. As a result, a high interest rate environment makes the household demand for deposits relatively inelastic allowing banks to charge a high spread s. On the other hand, low interest rate environments make cash a less expensive source of liquidity and households move towards ϵ, a number greater than 1. In other words, during low interest rate environments, the elasticity of demand for deposits is elastic and banks charge a low spread to avoid large outflows. I show in Appedix A.3 that the closed form solution for the bank's optimal deposit spread is:

$$s = \delta^{\frac{\epsilon}{\epsilon-1}} \left(\frac{\mathcal{M} - \rho}{\epsilon - \mathcal{M}} \right)^{\frac{1}{\epsilon-1}} i \tag{1.19}$$

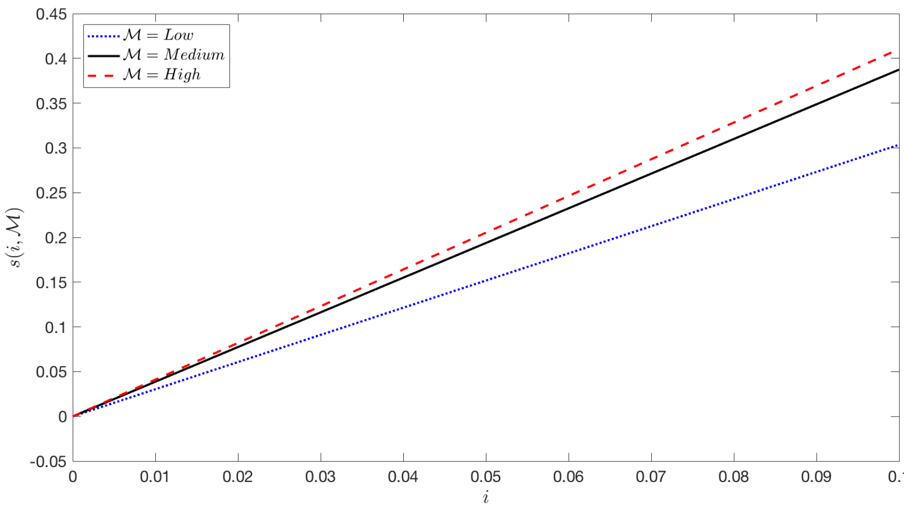


Figure 1.2: Deposit Spread

This is a plot of the aggregate deposit spread charged by the bank as a function of the nominal interest rate i. It is evaluated at low market power (dotted blue line), medium market power (black solid line), and high market power (red dotted line). I assume an elasticity of substitution between cash and deposits $\epsilon = 6.6077$, liquidity of deposits relative to cash $\delta = 0.10$, elasticity of substitution between wealth and liquidity services $\rho = 0.93$

Figure 1.2 plots the simulated aggregate deposit spread as a function of the nominal interest rate i. As in Drechsler et al. (2017), the spread $s(i, \mathcal{M})$ is increasing in the interest rate as well as in the market power. For a given nominal interest rate, higher values of market power $\mathcal{M}$, are associated with larger speads. This yields one implication of the model that can be tested empirically. Banks that are located in concentrated areas associated with greater market power charge a higher deposit spread and thus should face a smaller negative stock return response to monetary policy shocks. In the subsequent empirical section, I proxy $\mathcal{M}$ using Herfindahl-Hirschman index (HHI) of banks' share of the deposit market in each county.

1.5.3 Monetary Policy Effects

I now consider how monetary policy surprises can affect the bank's profit, which I proxy for stock prices. Using the envelope condition, we see that

$$\frac{d\pi}{di} = \mu E_0'(i) + (1 + \lambda^L)\left(S + \frac{\partial s(i, \mathcal{M})}{\partial i}\right) \tag{1.20}$$

Using the definition of μ, the multiplier on the budget constraint from above and substituting in, we get:

$$\frac{d\pi}{di} = (1 + \lambda^L)[S + \frac{\partial s(i, \mathcal{M})}{\partial i} + (1 + i)E_0'(i)] \tag{1.21}$$

Define the net interest margin NIM as:

$$\begin{aligned} NIM &= i^L L + iS - i^D D \\ \frac{dNIM}{di} &= S + \frac{\partial s(i, \mathcal{M})}{\partial i} \end{aligned} \tag{1.22}$$

Therefore, Equation 1.21 can be written as:

$$\frac{d\pi}{di} = \underbrace{(1 + \lambda^L)}_{\text{amplification}} [\underbrace{\frac{dNIM}{di}}_{\substack{\text{Net Interest Margin Channel} \\ \text{Positive}}} + (1 + i) \underbrace{E_0'(i)}_{\substack{\text{Capital-Gains Channel} \\ \text{Negative}}}] \tag{1.23}$$

From Equation 1.23, it is clear that bank profits will increase following a surprise tightening if the positive net-interest margin effect dominates the negative capital losses effect. If however, capital losses following interest rate increases are sufficiently large, bank profits will decline. Any sign switches in the stock price reaction to news about interest rates between pre-zero lower bound and during the zero lower bound can thus be attributed one channel dominating the other. λ^L, the Lagrangian multiplier, will magnify the response if the capital constraint binds ($\lambda^L > 0$). At this point, banks are unable to increase loans and must partially increase its holdings on safe assets S. With a higher holding of risky assets, banks will become more sensitive to monetary policy surprises through Equation 1.22. The net-interest margin also depends on the sensitivity of the spread with respect to the nominal interest rate which as I've shown in Figure 1.2 depends on the bank's market power $\mathcal{M}$.

The model I've described accounts for the event study results presented in Section 1.5, where the sensitivity of bank stock returns reversed prior to and during the zero lower bound. I found that prior to the zero lower bound, bank stock returns declined following a tightening surprise, which using Equation 1.23 must be attributed to capital losses dominating any increases in the net interest margin. During the zero lower bound, however, bank stock returns reacted positively which suggests that higher net interest margins dominated any capital losses that banks faced. As maturity transformers, banks benefit from a steeper yield curve because they fund long term assets by borrowing short term liabilities. Therefore, a testable implication not explicitly modeled is whether surprise increases in the slope of the yield curve dampen the capital losses channel for banks who engage heavily in maturity transformation. In other words, for banks that have a large maturity gap between their assets and liabilities, do steeper yield curve surprises dampen the negative effect of stock returns? In the next section, I test this cross-sectionally and find that the answer is yes which is in line with English et al. (2018a).

Returning to the capital constraint in Equation 1.4, one can interpret the term ψ^L as a coefficient of risk on loans whereby banks are constrained on a fraction of their loans that can be deemed risky. This constraint can arise from regulatory reasons which place limits on how much risk-taking a bank can engage in. A sufficient increase in ψ^L will bind Equation 1.4 ($\lambda^L > 0$) which can lead to an amplification effect on bank profits via Equation 1.23. A testable implication is whether increases in bank risk, magnify the response of bank returns to monetary policy surprises - a question that has not been addressed in the literature. I find that the answer is yes both before and during the zero-lower bound period.

Adding to the conversation of how the market power of banks can play a role in intermediation through its deposit rates (Drechsler et al. (2017)), I also test whether banks located in regions of higher concentration face an attenuated response to monetary policy shocks. The intuition can be found in Equation 1.22, where the sensitivity of a bank's net interest margin with respect to monetary policy surprises depends on the sensitivity of its deposit spread. Banks located in highly concentrated regions can charge a higher spread (lower deposit rate) than their counterparts in more competitve environments. This occurs because there are less opportunities for depositers to switch across banks in concentrated regions. Therefore, banks that behave more monopolistically, can pay a lower deposit rate and will face a less adverse shock to their returns. I test this implication by using county-level bank data and measuring the Herfindahl-Hirschman Index (HHI) of each county, I find that banks located in highly concetrated markets (large HHI) have about half the negative response in stock returns than banks located in highly competitive markets (low HHI).

In the next section, I empirically test the implications of the model by regressing bank stock returns on monetary policy shocks interacted with these different bank characteristics. The coefficient on this interaction term reveals whether bank heterogeneities produce different return sensitivities to monetary policy shocks. Furthermore, using a panel Vector Autogression along the lines of Vuolteenaho (2002), Campbell and Ammer (1993), and Bernanke and Kuttner (2005) I ask whether news about cash flows, expected returns, or real rates are driving these differential sensitivities. The underlying mechanism behind the reversal effect is that higher net interest margins dominate the negative effects of the discount rate channel. A decomposition of return sensitivities into news related to cash flows and discount rates would allow me to ascertain whether news about real rates dominated in the pre-ZLB and cash flow news dominated during the ZLB.

1.6 VAR Analysis

1.6.1 Components of Returns

Stock returns are driven by shocks to expected cash flows, discount rates, and expected returns. In studying the sensitivity of returns to policy shocks and why a sign change occurred, it is useful to decompose its change into these three different components in order to understand which piece is driving its variation. This decomposition began with Campbell and Ammer (1993) and Campbell and Shiller (1988a) who posited that movements in stock returns can be well summarized by the three components.

Three Components : Cash Flows, Expected Returns, and Real Rates

Despite most of the literature finding a negligible role of real interest rates in driving stock returns, it seems reasonable to include them for banks because of its inherent exposure to them. Movements in stock returns are assumed to be driven by changes in expectations of future cash flows, real interest rates, and expected returns. I follow Campbell and Shiller (1988a) and Bernanke and Kuttner (2005) who linearly decompose the excess equity returns into three components: (1) news about real interest rates, (2) dividends, and (3) future excess returns. I define the object of interest to be the bank holding period stock return y_{t+1}. This will have an unexpected return (e^y_{t+1}) which can be expressed as revisions in the expectation of discounted future dividends ($\tilde{e}^d_{t+1}$), the real interest rate ($\tilde{e}^r_{t+1}$), and future excess returns ($\tilde{e}^y_{t+1}$) [15].

$$e^y_{t+1} = \tilde{e}^d_{t+1} - \tilde{e}^r_{t+1} - \tilde{e}^y_{t+1} \tag{1.24}$$

This can be expressed as:

$$\begin{aligned}
\tilde{e}^d_{t+1} &= (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} \\
\tilde{e}^r_{t+1} &= (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j r_{t+1+j} \\
\tilde{e}^y_{t+1} &= (E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j y_{t+1+j}
\end{aligned} \tag{1.25}$$

where ρ is a discount factor that is set to 0.9962. Equation 1.24 is a dynamic accounting identity that comes from the basic definition of a holding period return and applying a log-linearization. It says that if the unexpected stock return is negative, then either expected future dividend growth is lower, expected future stock returns are higher, or expected future real interest rates are higher, or any of them. Suppose an asset with fixed dividends faces a decline in its price so that e^y_{t+1} is negative. This leads to a higher dividend yield and assuming no further capital losses, we should expect to see an increase in the asset's future return (i.e. a higher $\tilde{e}^y_{t+1}$). Therefore, Equation 1.24 is consistent. The discount rate ρ reflects the notion that increases of stock returns further out in the future is associated with a smaller decline in today's

[15] I provide a proof of this decomposition in Appendix A.4

stock price than increases closer to present day. Consider, for example, that there is news that stock returns will be higher ten periods from today. This must result in a large decline of the stock price today and subsequent smaller declines in the remaining nine periods. These subsequent declines mechanically reduce the required size of today's dropped stock price.

Estimating Equation 1.24 requires empirical proxies for the expectations in Equation 1.25 and I again follow the approach of Campbell and Ammer (1993) to model these expectations using a vector auto-regression (VAR). This monthly VAR includes six variables: the bank's stock returns, the real interest rate defined as the 3 month Treasury bill minus the log difference of nonseasonally adjusted CPI, the relative bill rate defined as the 6 month Treasury bill minus its 12 month moving average, the change in the six-month Treasury rate, the dividend-price ratio, and the Term Spread between a 10 Year Treasury rate and a 3 month bill. An individual bank's i state vector $z_{i,t}$ can be written as follows:

$$\begin{aligned} z_{i,t} &= \Gamma z_{i,t-1} + u_{i,t} \\ \Sigma &= E(u_{i,t}, u_{i,t}) \end{aligned} \tag{1.26}$$

I estimate Equation 1.26 by writing the components of Equation 1.24 as

$$\begin{aligned}
e^y_{t+1} &= e^y u_{i,t+1} \\
\tilde{e}^y_{t+1} &= \underbrace{e^y \rho\Gamma(1-\rho\Gamma)^{-1}}_{\lambda'} u_{i,t+1} \\
\tilde{e}^r_{t+1} &= e^r(1-\rho\Gamma)^{-1} u_{i,t+1} \\
\tilde{e}^d_{t+1} &= e^y_{t+1} + \tilde{e}^y_{t+1} + \tilde{e}^r_{t+1}
\end{aligned} \tag{1.27}$$

where e^y and e^r are $1 \times np$ selection matrices for the return and real interest rates, respectively. With this, I am able to assess the relative contributions of news about real interest rates, cash flows, and expected future returns to movements in the current stock return. There is, however, no monetary policy surprises in this framework, which is my main focus. In order to incorporate monetary policy surprises in this framework, I include the intradaily jumps during each FOMC meeting as an exogenous variable by aggregating them to the month and quarterly level. This allows me to identify the effects of monetary policy surprises on future expected returns within the VAR framework.

$$z_{i,t} = \Gamma z_{i,t-1} + \underbrace{\phi MPS_t + \omega_{i,t}}_{u_{i,t}} \tag{1.28}$$

where $\omega_{i,t}$ is orthogonal to the monetary policy surprise MPS_t and effectively decomposes the forecast error term $u_{i,t}$ into a component related to news about monetary policy ϕMPS_t and a component incorporating other news [16]. I estimate Equation

[16] Estimating ϕ, which is an n x 1 vector can be done in two ways. The first and most obvious way is to estimate Equation 1.28 directly by including MPS_t as an exogenous variable in the VAR.

1.28 which is a VAR augmented by a monetary policy surprise $ED4$.

We can rewrite Equation 1.27 as follows:

$$
\begin{aligned}
\tilde{e}^y_{t+1} &= \lambda'(\phi MPS_t + \omega_{i,t}) \\
\tilde{e}^r_{t+1} &= e^r(1-\rho\Gamma)^{-1}(\phi MPS_t + \omega_{i,t}) \\
\tilde{e}^d_{t+1} &= e^y(\phi MPS_t + \omega_{i,t}) + \lambda'(\phi MPS_t + \omega_{i,t}) + e^r(1-\rho\Gamma)^{-1}(\phi MPS_t + \omega_{i,t})
\end{aligned}
\tag{1.29}
$$

where again $\tilde{e}^d_{t+1}$ is calculated by backing out the response of expected returns and real rates. Taking the first derivative with respect to MPS_t in each of the expressions in Equation 1.29 will give the response of each component to a monetary policy surprise. In other words, I decompose the response of stock returns to monetary policy surprises into each of the respective components in order to assess which pieces of news is driving the overall response. I calculate the t-statistic by estimating standard errors using the delta method. Because I'm also interested in the heterogeneities of banks, I form portfolios of bank stock returns along three characteristics before and during the ZLB: maturity mismatch, risk, and market power. I consider banks in the lower and upper decile along each of the three characteristics which yields a total of six portfolios. These portfolios will be useful in understanding the differential impact of monetary policy for various bank characteristics. I estimate the derivatives of each

This, however, limits the sample period from 1984 to 2008, when monetary policy surprise data is available. A different method would be to do a two-stage regression where a pooled regression of $z_{i,t}$ is first run on its lag $z_{i,t-1}$ to estimate the coefficient matrix Γ. The second stage would then regress the VAR's 1-step ahead forecast errors $u_{i,t}$ on monetary policy surprises MPS_t to estimate ϕ. I take the first approach of including the shocks as an exogenous variable in the VAR.

expression in Equation 1.29 with respect to MPS_t and report the results in Table 1.4.

Table 1.4 presents the results of estimating the impact of monetary policy shocks on the news components, where the shaded blue line denotes the news components that dominates. In the pre-ZLB period (Panel 1.4a), I find that the negative effect of monetary policy shocks is due to news about real rates. This result differs from Bernanke and Kuttner (2005) who finds that for the aggregate stock market, news about future real rates don't matter and that most of the sensitivity is driven by future excess returns and cash flows. Turning over to the ZLB period (Panel 1.4b), I find that most of the sensitivity is driven from news about future cash flows. This result is in line with what we expect from the model's prediction that the reversed interest rate effect is generated when the increased benefits of net interest margin (cash flows) outweighs the negative capital loss effect (real rate). To my knowledge, the only paper that applies this decomposition to banks is Bredin et al. (2007). In their paper, they estimate the same decomposition, except they use data from the United Kingdom and consider different industries - one of which is the banking sector. They find that from 1975-2004, tightening surprises had a negative impact on news about dividends and expected excess returns, while having a positive impact on news related to real interest rates. My analysis is different because I consider banks along different characteristics (maturity, risk, and market power). The magnitudes of my estimates are also extremely large while the overall net effect is reasonable. A recent paper by Kontonikas et al. (2015) applies the same methodology to 10-year bonds and finds a similar implication that while the sensitivity of each news component is extremely large, the overall net effect is reasonable. I do not put much value on the magnitudes of each component, per-se, but rather use it to conclude that whereas news about the real interest rate dominated the pre-ZLB period, news about cash flows dominated the ZLB period. These magnitudes are backed out using the accounting identity in Equation 1.27.

1.6.2 Maturity Mismatch

I test the hypothesis that banks more heavily engaged in maturity transformation have an attenuated negative response to monetary policy surprises. The conventional business model of banks is to borrow at the short term interest rate through demand deposits and to lend at a higher rate in the form of loan issuance. The difference in rates is called the net-interest margin and is one measure of bank profitability. Using the conventional theory that banks benefit from a steep yield curve, I test whether cross sectional differences among banks' maturity gap play a key role explaining differences in reaction to monetary policy. It is important to emphasize that banks benefit from a steeping of the yield curve, which is a more specific type of monetary policy surprise. If there is a surprise level tightening however, it would seem that banks with long term fixed assets that have not yet matured would not benefit from higher interest income while also needing to pay out higher deposit rates through short term liabilities. Banks with a longer maturity gap, are in a sense, "locked-in" for a longer period of relatively low interest income, and would be hurt by this type of surprise. This would be the case for a shift in the *level* of interest rates as proxied by $MP1$. Rather than using $MP1$ as my shock, I am using $ED4$, which is a bet on the short term LIBOR rate four quarters ahead. This shock contains information on both the level and slope of the term structure and depending on the direction it affects banks with greater maturity mismatch, will inform me of which dimension of policy dominates. The interpretation is that banks with higher maturity gaps tend to benefit from steeper yield curves because they're able to extract higher interest income and pay lower deposit rates for a longer time. It is true that banks face immediate capital losses on their long maturity assets upon a slope tightening, but in subsequent periods, banks will reprice their loans at a higher rate. This latter effect is arguably more important, if we interpret stocks as representing the total sum of future discounted cash flows. In fact, Hanson and Stein (2015) finds evidence that when the yield curve steepens, banks increase the maturity of their security holdings. If the long end interest rates surprisingly rises while the short end falls, banks that engage in more maturity transformation are rewarded longer. It is this mechanism that I hope to capture in my regressions and the channel that English et al. (2018a) explores.

English et al. (2018a) applies a similar reasoning in an event study framework and finds that share prices of banks that engage heavily in maturity transformation have a significantly less negative response to tightening shocks. I find a similar result and conclude that $ED4$ contains information about the slope of the term structure which dominates any level effect. Using their framework, I define a maturity gap $T_{i,t}$ for bank i in quarter t as the difference in maturity between its asset and liability:

$$T_{i,t} = \Xi^A_{i,t} - \Xi^L_{i,t} \tag{1.30}$$

where $\Xi^A_{i,t}$ and $\Xi^L_{i,t}$ is the weighted average asset and liability repricing/maturity period in years, respectively. More specifically,

$$\begin{aligned} \Xi^A_{i,t} &= \frac{\sum_k m^k_A A^k_{i,t}}{\sum_k A^k_{i,t}} \\ \Xi^L_{i,t} &= \frac{\sum_k m^k_L L^k_{i,t}}{\sum_k L^k_{i,t}} \end{aligned} \tag{1.31}$$

where m^k_A is the maturity of asset category k, m^k_L is the maturity of liability category k, $A^k_{i,t}$ is asset k for bank i, and $L^k_{i,t}$ is liability k for bank i. The value captures how much longer it takes assets to mature before liabilities.

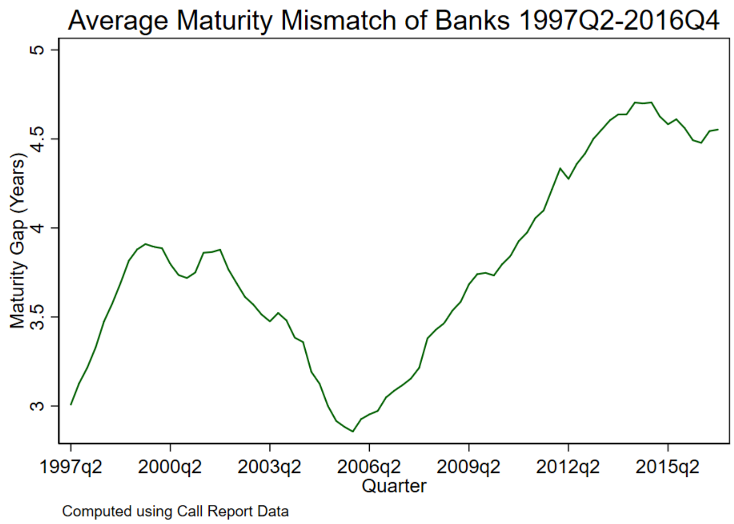


Figure 1.3: Average Maturity Gap $\bar{T}$ across all banks

For each bank i and quarter t in my sample, I compute its maturity gap $T_{i,t}$. Details of this calculation is provided in Data Appendix A.7. Figure 1.3 plots a time series of the average maturity gap $\bar{T}$ across all banks in each quarter. The time series pattern shows a gradual increase in the gap from 1997 to early 2000 followed by a decline through 2005. There is also an upward trend from 2005 to 2015 reflecting the growing difference between the maturity of assets and liabilities of average bank balance sheet. I then consider the bottom and top decile of banks by their maturity gap to test the hypothesis that banks that have greater maturity mismatches face a smaller decline in their stock returns. The average maturity gap $T_{i,t}$ in my sample is 3.14 years which mean that bank assets face an approximately 3 year greater maturity than their liabilities. The first decile is 1.375 years and the top decile is 5.98 years.

I test the implication using a cross-sectional regression and interact monetary policy surprises with the bank's maturity gap which is an empirical approach similar to English et al. (2018a)[17]. Because bank balance sheets are quarterly, I take an average across monthly bank returns and monetary policy surprises over the quarter. The quarterly monetary policy surprises are interacted with the quarterly balance sheet variables. An important distinction between this specification and English et al. (2018a) is that their dependent variable is the two hour intradaily return while their interaction variable is quarterly. Under this methodology, many bank stock returns will be associated with the same quarterly balance sheet variable, making variation in maturity gap non-existent. The interaction regression is derived as follows:

$$
\begin{aligned}
R_{i,t} &= \beta_i MPS_t + \epsilon_{i,t} \\
\beta_i &= \gamma_0 + \gamma_1 T_{i,t} \\
R_{i,t} &= \gamma_0 MPS_t + \gamma_1 T_{i,t} \times MPS_t + \epsilon_{i,t}
\end{aligned}
\tag{1.32}
$$

where the last line of Equation 1.32 comes from a simple substitution of β_i. A positive coefficient on the interaction term $T_{i,t} \times MPS_t$ supports the notion of an attenuated effect for banks with higher maturity mismatch. I document the results in Table 1.5a, where a one year greater maturity gap leads to an attenuation of 1.83%. English et al. (2018a) find an attenuated effect of 46 basis points over a two-hour interval. Although having an attenuated effect, banks seem to benefit only in a relative sense because overall stock returns are still negative in response to tightening shocks. Despite

[17] English et al. (2018a), however, also includes a variety of other characteristics such as demand deposits, savings deposits, and leverage

using different measurement horizons of variables, I am still able to capture the same implication as English et al. (2018a).

Table 1.6 compares the effects of monetary policy shock during the pre-ZLB period for banks with low maturity mismatches (Table 1.6a) and those with large maturity mismatches (Table 1.6b) in a VAR setting. The contemporaneous effect of monetary policy surprises on stock returns for the lowest decile by maturity gaps is -17 % which is over double that for the highest decile of maturity gap -5.45 %. The attenuated effect of bank stock return sensitivity to tightening surprises for banks with larger maturity gaps is in line with the result found by English et al. (2018a) and supports the notion that banks benefit from a steeper yield curve. In the ZLB period, we find a similar attenuation, although the sign is reversed and positive (Table 1.7) much like the reversal effect discussed earlier.

1.6.3 Bank Risk

Bank risk has been advent in the conversation of financial regulation since The Dodd-Frank Wall Street Reform and Consumer Protection Act. Since the first Basel Accord in 1988, banks have had to categorize their assets into different risk categories in order to ensure adequate capital in events of unexpected losses. In the wake of the financial crisis, Basel III of 2010 redesigned capital requirements by including minimum amounts of common equity and liquidity ratios. The measurement and pricing of risk is fundamental in finance and few papers have related how its presence in banks can lead to differences in the transmission mechanism [18]. Instead, much of the literature has focused on the impact of changes in interest rates on risk perceptions and tolerance of firms, a phenomenon known as the "risk-taking" channel [19]. Instead, I take the riskiness of assets as given and ask how this can give rise to differential responses of stock returns to monetary policy surprises.

Riskier banks tend to hold assets which are less likely to pay off during times of higher interest rates. By lending to high-risk borrowers, these banks optimally choose to take on greater risk while satisfying capital requirements. However, these banks also face a higher probability of losing value upon tightening which feeds into market perceptions on expected future cash flows. To the extent that bank stock returns reflect news about future cash flows, we expect that banks which tend to be riskier, to face a larger decline in their stock price upon a surprise tightening. Banks that hold a higher fraction of risky loans will have a harder time receiving interest payments and this feeds into a lower expectation of paying dividends to its shareholders. In the model of Section 1.5.3 and Equation 1.23, it is clear that when banks increase the fraction of risky loans which binds their capital constraint, there will exist an amplification effect as given by the Lagrangian $(1+\lambda^L)$. I test the hypothesis that banks which tend to be riskier, as defined by their balance sheet, tend to have a larger drop in their stock returns upon monetary policy tightening shocks.

I measure bank risk by the amount of high risk loans as a percentage of Tier-1

[18]There has been a literature on the impact of capital standards on risk-taking by banks. (Santos (2001))

[19]See Borio and Zhu (2012) for an overview of the risk-taking channel of monetary policy

capital. Tier-1 capital is the most loss-absorbing form of capital and includes the value of its common stock, retained earnings, and accumulated other comprehensive income (AOCI). During times of financial distress, Tier-1 capital is the first to absorb losses followed by other debt holders and investors. Accordingly, the amount of Tier-1 capital signifies to shareholders how prepared a bank is to face unexpected losses. High risk loans is reported on the Call Report and includes commercial and industrial loans, nonfarm nonresidential properties secured by real estate, multi-family residential loans, and construction land developments secured by real estate. While the item does not clearly define why it is high risk, presumably, banks assess the borrower's credit score, future business earnings, and other metrics in labeling the loan to be of "high risk". After computing my risk measure for each bank, I estimate an interaction regression similar to Equation 1.32 except allow β_i to depend on $RISK$. The results in Table 1.5b suggests that banks with a 1% higher fraction of high risk loans face a greater negative response of 20% - thus confirming the amplification effect from the model. Column (2) of Table 1.5b also shows the reversal effect during the ZLB period.

I also estimate for the bottom and top decile by risk, the contemporaneous effects of monetary policy surprises on stock returns in a VAR setting (Equation 1.28). Table 1.8 estimates the 6 variable panel VAR by including the fourth eurodollar futures contract $ED4_t$ as an exogenous monetary policy surprise. As the top panel shows (Table 1.8a), a 100 basis point tightening surprise corresponds to a decline of 3.2 %

in the stock returns of banks with a low risk to capital ratio. On the other hand, the bottom panel (Table 1.8b) reports a 10 % decline in stock returns for high risk banks - a magnitude much larger than that of low risk banks. This result points towards evidence that high risk banks, which contain loan portfolios that are more susceptible to default or late payment, are hurt more by monetary policy tightening surprises and is in line with the amplified effect suggested by my model. This could perhaps be due to heightened uncertainty about future cash flows of riskier institutions. Turning over to the ZLB period (Table 1.9), I find that there is a reversal effect, although riskier banks do not benefit as much from tightening surprises.

1.6.4 Market Power

As illustrated by the model and in Figure 1.2, banks that have greater market power tend to charge larger deposit spreads to their customers. This allows them to generate larger profits without losing their customer base to other banks. As an empirical proxy for market power, I calculate the total amount of deposits for each county and each quarter in the United States. I then compute each bank's share of this total which represents its deposit market share. In order to compute the HHI, I sum the squared deposit market share of all banks that operate branches in a given county in a given quarter, and average over all quarters. Each bank is then assigned the HHI of the county of which it is located. A higher HHI indicates more market concentration (monopoly) and a lower index represents more competitive markets.

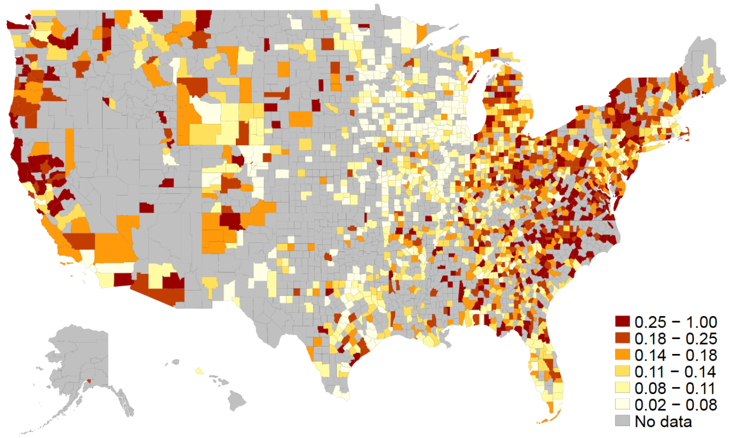


Figure 1.4: Market Power Across the United States

This is a figure which describes the market power as proxied by the HHI Index across the United States at the county level. Data on county level deposits are from the Call Report data set.

Figure 1.4 shows the distribution of HHI indices across counties in the United States with most of the market power concentrated on the East and West coasts. I estimate a panel VAR on the top decile of banks that have large market power and bottom decile located in more competitive environments. I test the hypothesis that those located in more concentrated regions charge a higher spread and therefore are hurt less by monetary policy surprises than their counterparts who are unable to charge depositors a high spread. This again comes from Equation 1.22 which shows that banks in more concentrated areas have a higher positive effect of tightening on their net interest margin. I estimate Equation 1.32 using HHI as an interaction variable and document the results in Table 1.5c. The results suggest that banks located in a perfectly competitive market that transition to a monopolistic one face a 7% smaller negative response on their stock returns. This dampening of the negative impact from shocks confirms the intuition of the model and Equation 1.22 which states that banks with greater market power benefit from charger higher spreads.

Table 1.10a provides VAR evidence and reports that a 100 basis point surprise tightening is associated with a 6 % decline for banks located in the bottom decile of market power. Moving towards the top decile for banks located in more monopolistic regions, Table 1.10b reports that the sensitivity is reduced to half at 3%. This attenuated response suggests that banks located in more concentrated areas benefit more than banks with more competitive deposit markets.

1.7 Conclusion

In this paper, I have documented that the sensitivity of bank stock returns reversed from negative during the pre-ZLB period to positive during the ZLB. The theory of Brunnermeier and Koby (2018) suggests that the sign of this effect depends on whether the positive effect of higher net interest margins or the negative effect from capital losses (discount rate channel) dominates. I find that while during the pre-ZLB, bank stock returns were mostly driven by news about real interest rates, this became dominated by news about future cash flows during the ZLB - a result in line with the reversal effect. Furthermore, I augment their model with the deposit channel of policy by Drechsler et al. (2017) to draw implications on how return sensitivity to monetary policy can depend on bank characteristics. I confirm these implications by showing that banks with greater maturity mismatch and market power face a smaller decline in their stock returns and banks that are riskier face a greater decline. The results in this paper serve as evidence that banks are institutions that are uniquely impacted by monetary policy.

(a) Pre-ZLB (1984Q1-2008Q4)

	Low MM	High MM	Low Risk	High Risk	Low HHI	High HHI
$\tilde{x}^d_{MP}$	0.947**	0.106**	0.586**	0.617***	0.692**	0.480**
	(0.459)	(0.0503)	(0.246)	(0.284)	(0.332)	(0.243)
$\tilde{x}^r_{MP}$	1.11**	0.193	0.605***	0.823	0.761**	0.515**
	(0.454)	(0.150)	(0.227)	(0.652)	(0.333)	(0.240)
$\tilde{x}^y_{MP}$	0.0034***	-0.0286***	0.0142***	-0.104***	-0.0005	-0.0016***
	(0.0011)	(0.004)	(0.0028)	(0.036)	(0.0008)	(0.0006)
Total Effect	-0.170	-0.0584	-0.0332	-0.102	-0.0676	-0.0334

(b) ZLB (2009Q1-2016Q4)

	Low MM	High MM	Low Risk	High Risk	Low HHI	High HHI
$\tilde{x}^d_{MP}$	2.12***	0.175**	0.361**	1.270***	0.0670*	3.889
	(0.671)	(0.0890)	(0.185)	(0.398)	(0.0342)	(2.70)
$\tilde{x}^r_{MP}$	0.446	-0.0154	0.139	0.856**	0.0723**	0.862
	(0.564)	(0.0350)	(0.748)	(0.370)	(0.0293)	(1.460)
$\tilde{x}^y_{MP}$	1.565*	0.0900	0.0653	0.120***	-0.0066	2.97
	(0.923)	(0.090)	(0.143)	(0.0352)	(0.0105)	(2.093)
Total Effect	0.109	0.100	0.157	0.294	0.0012	0.0570

Table 1.4: The Impact of Monetary Policy Shocks on News about Cash Flows, Real Rates, and Expected Excess Returns

This table presents the estimated response of the three components of bank stock returns to monetary policy shocks ($ED4$). $\tilde{x}^d_{MP}$ is news related to cash flows, $\tilde{x}^r_{MP}$ is news related to real rates, and $\tilde{x}^y_{MP}$ is news related to expected future excess returns. News components are extracted from the VAR with lag 1. The state vector of this VAR is given by $[y_t \quad r_t \quad REL_t \quad \Delta r_t \quad DIV/PRICE_t \quad TERMSPREAD_t]$, where y_t is the stock return, r_t is the 3 month interest rate, REL_t is the 6 month rate minus its 12 month moving average, Δr_t is the change in the 6 month rate, $DIV/PRICE_t$ is the dividend price ratio, and $TERMSPREAD_t$ is the difference between the 10 year rate and 4 month rate. Panel 1.4a considers the pre-zero lower bound period (1984Q1-2008Q4) and Panel 1.4b considers the zero lower bound period (2009Q1-2016Q4). Each column corresponds to banks with characteristics in the bottom decline (Low) and top decile (High). The characteristics are MM (Maturity Mismatch), Risk (Risk as defined on Call Report), Herfindahl-Hirschman Index (HHI). The light blue shaded rows are used to illustrate which component of news is driving the response to monetary policy shocks. The standard errors in parentheses are computed using the delta method.

(a) Bank Stock Returns and Interaction with Maturity Mismatch

	(1) Pre-ZLB 1984Q1-2008Q4	(2) ZLB 2009Q1-2016Q4
MPS	-0.113***	0.152***
	(0.0125)	(0.0326)
$T_{i,t} \times MPS$	0.0183***	-0.0316
	(0.00308)	(0.0621)
Constant	-0.00594***	0.0417***
	(0.00129)	(0.00213)
Observations	28371	6367
R^2	0.0158	0.0604
Controls	Yes	Yes

(b) Bank Stock Returns and Interaction with Risk

	(1) Pre-ZLB 1984Q1-2008Q4	(2) ZLB 2009Q1-2016Q4
MPS	-0.0396***	0.151***
	(0.00944)	(0.0271)
$RISK_{i,t} \times MPS$	-0.203***	0.235
	(.0810)	(0.574)
Constant	-0.00692***	0.0499***
	(0.000985)	(0.00286)
Observations	31105	6779
R^2	0.0217	0.123
Controls	Yes	Yes

(c) Bank Stock Returns and Interaction with Market Power

	(1) Pre-ZLB 1984Q1-2008Q4	(2) ZLB 2009Q1-2016Q4
MPS	-0.0654***	0.0747*
	(0.0133)	(0.0436)
$HHI_{i,t} \times MPS$	0.0783***	-0.0535
	(0.0245)	(0.0631)
Constant	-0.00696***	0.0529***
	(0.00105)	(0.00300)
Observations	30965	6772
R^2	0.0157	0.0530
Controls	Yes	Yes

Table 1.5: Return and MPS Interaction Regression

This table reports the results estimating a regression of bank stock returns on a monetary policy shock proxied by $ED4$, and an interaction of the shock with bank characteristics. The dependent variable is the average of monthly returns over a particular quarter. The monetary policy surprises are averaged over a quarter and interacted with computed bank balance sheet information from Call Reports published in the same quarter. $T_{i,t}$ is the proxy for maturity gap as is defined as the difference in weighted (by asset) maturity between assets and liabilities. $RISK_{i,t}$ is defined as the ratio of high risk loans as a percentage of capital. HHI, the Herfindahl-Hirschman Index, is a proxy of market power of deposit share.

(a) VAR Coefficient Matrix: **Bottom Decile** by Maturity Gap

	y_{t-1}	r_{t-1}	$RELATIVE_{t-1}$	Δr_{t-1}	$Dividend : Price_{t-1}$	$TERMSPREAD_{t-1}$	MPS_t
y_t	**-0.00383**	**-0.000300****	**0.00524*****	**-0.0294*****	**0.00141**	**0.00847*****	$\boxed{\textbf{-0.170}^{***}}$
	(0.0140)	(0.000124)	(0.000663)	(0.00310)	(0.00137)	(0.000316)	(0.0116)
r_t	**0.363*****	**0.986*****	**0.104*****	**1.24*****	**0.00356**	**0.0378*****	**1.552*****
	(0.0554)	(0.000666)	(0.00335)	(0.0183)	(0.00538)	(0.00177)	(0.0818)
$RELATIVE_t$	**0.304*****	**-0.0186*****	**0.586*****	**1.57*****	**0.00716**	**0.0522*****	**1.906*****
	(0.0599)	(0.000693)	(0.00434)	(0.0211)	(0.00594)	(0.00214)	(0.0824)
Δr_t	**0.243*****	**-0.00733*****	**0.0293*****	**0.103*****	**0.00585**	**0.0182*****	**1.022*****
	(0.0319)	(0.000366)	(0.00239)	(0.0102)	(0.00450)	(0.00108)	(0.0434)
$Dividend : Price_t$	**0.0123**	**0.00132****	**-0.00247**	**0.00174**	**-0.000336**	**0.00129**	**0.0127**
	(0.0316)	(0.000545)	(0.00263)	(0.00468)	(0.00149)	(0.00150)	(0.0819)
$TERMSPREAD_t$	**0.0935***	**0.0200*****	**-0.330*****	**-0.186*****	**0.0133**	**0.922*****	**0.662*****
	(0.0553)	(0.000658)	(0.00430)	(0.0198)	(0.0129)	(0.00188)	(0.0866)

(b) VAR Coefficient Matrix: **Top Decile** by Maturity Gap

	y_{t-1}	r_{t-1}	$RELATIVE_{t-1}$	Δr_{t-1}	$Dividend : Price_{t-1}$	$TERMSPREAD_{t-1}$	MPS_t
y_t	**-0.0247**	**0.00128*****	**-0.00198****	**0.0109*****	**-0.000132**	**0.00493*****	$\boxed{\textbf{-0.0545}^{***}}$
	(0.0188)	(0.000196)	(0.000935)	(0.00310)	(0.00687)	(0.000571)	(0.0107)
r_t	**-0.975*****	**0.966*****	**0.128*****	**0.596*****	**-0.101*****	**0.0770*****	**4.112*****
	(0.111)	(0.00126)	(0.00767)	(0.0196)	(0.0331)	(0.00382)	(0.0967)
$RELATIVE_t$	**-1.010*****	**-0.0408*****	**0.703*****	**0.680*****	**-0.0612*****	**0.0958*****	**4.372*****
	(0.105)	(0.00124)	(0.00745)	(0.0182)	(0.0271)	(0.00393)	(0.0922)
Δr_t	**-0.619**	**-0.0169**	**0.0857**	**-0.304**	**-0.00648**	**0.0370**	**2.028**
	(0.0580)	(0.00069)	(0.00431)	(0.0134)	(0.0185)	(0.00195)	(0.0535)
$Dividend : Price_t$	**-0.238**	**0.00327**	**-0.0119**	**0.0202**	**0.115**	**-0.0149**	**-0.406**
	(0.258)	(0.00283)	(0.0113)	(0.0166)	(0.170)	(0.0157)	(0.426)
$TERMSPREAD_t$	**-0.324****	**-0.00172**	**-0.0961*****	**-0.545*****	**0.101**	**0.912*****	**-2.761*****
	(0.116)	(0.00186)	(0.00679)	(0.0279)	(0.0816)	(0.00490)	(0.0905)

Table 1.6: Quarterly Bank VAR Pre-ZLB Estimates for 1984Q1-2008Q4 including Monetary Policy Surprises by Maturity Mismatch

Panel (a) reports the VAR Coefficient Matrix of the bottom decile by maturity gap for estimating Equation 1.28 using OLS pooled regressions for each state variable and including monetary policy surprises MPS_t as an exogenous variable. The six state variables are y_t (stock return), r_t (3 month interest rate), $RELATIVE_t$ (6 month rate minus its 12 month moving average), Δr_t (change in the 6 month rate), $Dividend : Price_t$ (dividend price ratio), and $TERMSPREAD_t$ (the difference between the 10 year rate and 3 month rate). The number in **bold** is the regression coefficient and the number in parenthesis is a robust standard error. Panel (b) reports VAR Coefficient Matrix of the top decile by maturity gap for estimating Equation 1.28 with a two-step regression. *, **, *** denote significance at the 10%, 5%, and 1% level respetively

(a) VAR Coefficient Matrix: **Bottom Decile** by Maturity Gap

	y_{t-1}	r_{t-1}	$RELATIVE_{t-1}$	Δr_{t-1}	$Dividend:Price_{t-1}$	$TERMSPREAD_{t-1}$	MPS_t
y_t	**-0.0784****	**0.00837**	**-0.00464**	**0.0467**	**-0.01001**	**0.00317****	$\boxed{\textbf{0.109}^{***}}$
	(0.0371)	(0.0243)	(0.00684)	(0.0295)	(0.147)	(0.00137)	(0.0527)
r_t	**-0.0367***	**0.885*****	**0.0351*****	**0.154*****	**0.460****	**0.00408*****	**-0.223*****
	(0.0219)	(0.0246)	(0.00409)	(0.0266)	(0.190)	(0.00121)	(0.0707)
$RELATIVE_t$	**0.0742****	**-0.282*****	**0.673*****	**0.342*****	**0.116**	**0.0140*****	**-0.725*****
	(0.0255)	(0.0190)	(0.0451)	(0.0234)	(0.191)	(0.00143)	(0.0857)
Δr_t	**-0.00237**	**-0.117*****	**0.0214*****	**-0.275*****	**0.201**	**0.00513*****	**0.251*****
	(0.00892)	(0.00885)	(0.00138)	(0.0109)	(0.0942)	(0.000722)	(0.0423)
$Dividend:Price_t$	**-0.00754**	**0.00246**	**-0.000409**	**-0.00553**	**0.222*****	**0.00117*****	**-0.00951**
	(0.00572)	(0.00335)	(0.000762)	(0.00425)	(0.0630)	(0.000195)	(0.00934)
$TERMSPREAD_t$	**0.802*****	**0.475*****	**-0.545*****	**1.820*****	**0.444**	**0.939*****	**1.847*****
	(0.158)	(0.144)	(0.261)	(0.106)	(1.065)	(0.0832)	(0.307)

(b) VAR Coefficient Matrix: **Top Decile** by Maturity Gap

	y_{t-1}	r_{t-1}	$RELATIVE_{t-1}$	Δr_{t-1}	$Dividend:Price_{t-1}$	$TERMSPREAD_{t-1}$	MPS_t
y_t	**-0.0600***	**0.0327***	**-0.000925**	**0.0426**	**0.0557**	**0.00327****	$\boxed{\textbf{0.100}^{**}}$
	(0.0310)	(0.0164)	(0.00553)	(0.0278)	(0.0924)	(0.000858)	(0.0348)
r_t	**0.0130**	**0.928*****	**0.0331*****	**0.210*****	**0.0344**	**0.00330*****	**-0.179*****
	(0.0264)	(0.218)	(0.00346)	(0.0315)	(0.0962)	(0.000895)	(0.0580)
$RELATIVE_t$	**0.119*****	**-0.226*****	**0.661*****	**0.358*****	**-0.128**	**0.0119*****	**-0.461*****
	(0.0338)	(0.0164)	(0.0674)	(0.027)	(0.118)	(0.00115)	(0.0732)
Δr_t	**0.000723**	**-0.115****	**0.0204*****	**-0.249*****	**0.0172**	**0.00548*****	**0.228*****
	(0.0104)	(0.0690)	(0.00965)	(0.0987)	(0.0494)	(0.000623)	(0.0391)
$Dividend:Price_t$	**-0.00522**	**-0.00840**	**0.00427**	**-0.00855**	**0.193**	**0.00373*****	**-0.00660**
	(0.0114)	(0.0131)	(0.00264)	(0.0153)	(0.146)	(0.000670)	(0.0564)
$TERMSPREAD_t$	**0.931***	**0.372*****	**-0.507*****	**1.647*****	**0.726**	**0.947*****	**1.638*****
	(0.207)	(0.116)	(0.226)	(0.111)	(0.748)	(0.065)	(0.242)

Table 1.7: Quarterly Bank VAR ZLB Estimates for 2009Q1-2016Q4 including Monetary Policy Surprises by Maturity Mismatch

Panel (a) reports the VAR Coefficient Matrix of the bottom decile by maturity gap for estimating Equation 1.28 using OLS pooled regressions for each state variable and including monetary policy surprises MPS_t as an exogenous variable. The six state variables are y_t (stock return), r_t (3 month interest rate), $RELATIVE_t$ (6 month rate minus its 12 month moving average), Δr_t (change in the 6 month rate), $Dividend : Price_t$ (dividend price ratio), and $TERMSPREAD_t$ (the difference between the 10 year rate and 3 month rate). The number in **bold** is the regression coefficient and the number in parenthesis is a robust standard error. Panel (b) reports VAR Coefficient Matrix of the top decile by maturity gap for estimating Equation 1.28 with a two-step regression. *, **, *** denote significance at the 10%, 5%, and 1% level respetively

(a) VAR Coefficient Matrix: **Bottom Decile** by Bank Risk

	y_{t-1}	r_{t-1}	$RELATIVE_{t-1}$	Δr_{t-1}	$Dividend:Price_{t-1}$	$TERMSPREAD_{t-1}$	MPS_t
y_t	**-0.0823****	**0.00198*****	**-0.000556**	**0.0182****	**-0.138***	**0.00426*****	$\boxed{\textbf{-0.0326}^{*}}$
	(0.0299)	(0.00028)	(0.00179)	(0.00871)	(0.0738)	(0.00056)	(0.0181)
r_t	**0.174**	**0.982*****	**0.173*****	**0.996*****	**-2.094***	**0.0533*****	**2.099*****
	(0.114)	(0.00191)	(0.00876)	(0.0464)	(1.022)	(0.00338)	(0.139)
$RELATIVE_t$	**0.0106**	**-0.0265*****	**0.695*****	**1.216*****	**-1.895***	**0.0743*****	**1.799*****
	(0.111)	(0.00192)	(0.0107)	(0.0544)	(0.972)	(0.00360)	(0.146)
Δr_t	**-0.0354**	**-0.0115*****	**0.0862*****	**-0.0583****	**-0.902***	**0.0299*****	**0.785*****
	(0.0618)	(0.00101)	(0.00559)	(0.0284)	(0.528)	(0.00187)	(0.0758)
$Dividend:Price_t$	**-0.0199*****	**0.00111*****	**0.000464**	**-0.00246****	**0.141**	**0.00140*****	**-0.00358**
	(0.00290)	(0.000133)	(0.000331)	(0.000932)	(0.108)	(0.000284)	(0.00220)
$TERMSPREAD_t$	**-0.471*****	**0.00779*****	**-0.258*****	**-0.403*****	**2.22****	**0.925*****	**-1.350*****
	(0.108)	(0.00207)	(0.00920)	(0.0461)	(0.917)	(0.00438)	(0.120)

(b) VAR Coefficient Matrix: **Top Decile** by Bank Risk

	y_{t-1}	r_{t-1}	$RELATIVE_{t-1}$	Δr_{t-1}	$Dividend:Price_{t-1}$	$TERMSPREAD_{t-1}$	MPS_t
y_t	**-0.00159**	**-0.0000714**	**0.00182**	**-0.0133**	**-0.00988**	**0.00589*****	$\boxed{\textbf{-0.102}^{***}}$
	(0.0352)	(0.000339)	(0.00216)	(0.00830)	(0.0111)	(0.000948)	(0.0255)
r_t	**0.243****	**0.981*****	**0.109*****	**0.916*****	**0.0353**	**0.0494*****	**3.514*****
	(0.123)	(0.00186)	(0.0137)	(0.0484)	(0.0371)	(0.00572)	(0.228)
$RELATIVE_t$	**0.193**	**-0.0246*****	**0.637*****	**1.142*****	**0.0326**	**0.0633*****	**3.651*****
	(0.140)	(0.00199)	(0.0161)	(0.0563)	(0.0305)	(0.00638)	(0.239)
Δr_t	**0.0601**	**-0.0109*****	**0.0533*****	**-0.0929****	**0.0274****	**0.0255*****	**1.703*****
	(0.0737)	(0.00105)	(0.00894)	(0.0332)	(0.0125)	(0.00334)	(0.127)
$Dividend:Price_t$	**-000553**	**-0.00121**	**0.00760**	**-0.0120**	**0.00876**	**0.00821**	**-0.0987**
	(0.0493)	(0.00217)	(0.00614)	(0.0193)	(0.0150)	(0.00747)	(0.219)
$TERMSPREAD_t$	**-0.0114**	**0.00872*****	**-0.219*****	**-0.340*****	**-0.0621**	**0.924*****	**-1.627*****
	(0.161)	(0.00242)	(0.0146)	(0.0616)	(0.0721)	(0.00677)	(0.197)

Table 1.8: Quarterly Bank VAR Estimates Pre-ZLB for 1984Q1-2008Q4 including Monetary Policy Surprises by Bank Risk

Panel (a) reports the VAR Coefficient Matrix of the bottom decile by bank risk for estimating Equation 1.28 using OLS pooled regressions from 1984Q1-2008Q4 for each state variable and including monetary policy surprises MPS_t as an exogenous variable. The six state variables are y_t (stock return), r_t (3 month interest rate), $RELATIVE_t$ (6 month rate minus its 12 month moving average), Δr_t (change in the 6 month rate), $Dividend : Price_t$ (dividend price ratio), and $TERMSPREAD_t$ (the difference between the 10 year rate and 3 month rate). The number in **bold** is the regression coefficient and the number in parenthesis is a robust standard error. Panel (b) reports the VAR Coefficient Matrix of the top decile by bank risk for estimating Equation 1.28. *, **, *** denote significance at the 10%, 5%, and 1% level respetively

(a) VAR Coefficient Matrix: **Bottom Decile** by Bank Risk

	y_{t-1}	r_{t-1}	$RELATIVE_{t-1}$	Δr_{t-1}	$Dividend : Price_{t-1}$	$TERMSPREAD_{t-1}$	MPS_t
y_t	**-0.0212**	**0.00924**	**-0.0193****	**0.0302**	**0.894****	**0.00165**	$\boxed{\textbf{0.157}^{***}}$
	(0.0318)	(0.0161)	(0.00793)	(0.0404)	(0.379)	(0.00116)	(0.0354)
r_t	**-0.0810*****	**0.911*****	**0.0333*****	**0.292*****	**1.378*****	**0.00209****	**-0.242*****
	(0.0248)	(0.182)	(0.00464)	(0.0392)	(0.334)	(0.00101)	(0.0603)
$RELATIVE_t$	**0.116*****	**-0.220*****	**0.661*****	**0.371*****	**0.184**	**0.0118*****	**-0.356*****
	(0.0310)	(0.0165)	(0.0864)	(0.0337)	(0.389)	(0.00117)	(0.0762)
Δr_t	**-0.0165**	**-0.133*****	**0.0228*****	**-0.238****	**1.026***	**0.00480*****	**0.248*****
	(0.0106)	(0.0667)	(0.0185)	(0.0125)	(0.194)	(0.000588)	(0.0388)
$Dividend : Price_t$	**-0.000824**	**0.000140**	**0.00349*****	**-0.0103****	**0.621*****	**0.000758*****	**-0.00925*****
	(0.00287)	(0.00148)	(0.000709)	(0.00404)	(0.0910)	(0.000135)	(0.00248)
$TERMSPREAD_t$	**1.584*****	**0.299*****	**-0.485*****	**1.177*****	**10.850****	**0.930*****	**2.358*****
	(0.190)	(0.0997)	(0.0327)	(0.157)	(2.44)	(0.0687)	(0.250)

(b) VAR Coefficient Matrix: **Top Decile** by Bank Risk

	y_{t-1}	r_{t-1}	$RELATIVE_{t-1}$	Δr_{t-1}	$Dividend : Price_{t-1}$	$TERMSPREAD_{t-1}$	MPS_t
y_t	**-0.0345**	**-0.0118**	**-0.00230**	**-.0668****	**0.0209**	**0.00442****	$\boxed{\textbf{0.293}^{**}}$
	(0.0453)	(0.0280)	(0.00686)	(0.0249)	(0.0955)	(0.00149)	(0.0587)
r_t	**0.0173**	**0.750*****	**0.0140**	**0.0645*****	**0.0135**	**0.00789*****	**-0.0706**
	(0.0304)	(0.0650)	(0.00968)	(0.0311)	(0.0905)	(0.00206)	(0.0764)
$RELATIVE_t$	**0.0448**	**-0.359*****	**0.663*****	**0.357*****	**-0.122**	**0.0167*****	**-0.850*****
	(0.0313)	(0.0311)	(0.0490)	(0.0245)	(0.0994)	(0.00166)	(0.0887)
Δr_t	**-0.00499**	**-0.116*****	**0.0183*****	**-0.273****	**0.0219***	**0.00453*****	**0.217*****
	(0.00963)	(0.0134)	(0.00165)	(0.108)	(0.03708)	(0.000757)	(0.0416)
$Dividend : Price_t$	**-0.0246**	**-0.00162**	**-0.000490**	**-0.00621**	**-0.0190**	**0.0216*****	**-0.0389**
	(0.0342)	(0.0145)	(0.00467)	(0.0151)	(0.0637)	(0.00557)	(0.0395)
$TERMSPREAD_t$	**0.468****	**0.354**	**-0.530*****	**1.978*****	**-0.433****	**0.955*****	**1.546*****
	(0.229)	(0.253)	(0.0415)	(0.110)	(0.517)	(0.106)	(0.359)

Table 1.9: Quarterly Bank VAR Estimates ZLB for 2009Q1-2016Q4 including Monetary Policy Surprises by Bank Risk

Panel (a) reports the VAR Coefficient Matrix of the bottom decile by bank risk for estimating Equation 1.28 using OLS pooled regressions from 1984Q1-2008Q4 for each state variable and including monetary policy surprises MPS_t as an exogenous variable. The six state variables are y_t (stock return), r_t (3 month interest rate), $RELATIVE_t$ (6 month rate minus its 12 month moving average), Δr_t (change in the 6 month rate), $Dividend : Price_t$ (dividend price ratio), and $TERMSPREAD_t$ (the difference between the 10 year rate and 3 month rate). The number in **bold** is the regression coefficient and the number in parenthesis is a robust standard error. Panel (b) reports the VAR Coefficient Matrix of the top decile by bank risk for estimating Equation 1.28. *, **, *** denote significance at the 10%, 5%, and 1% level respetively

(a) VAR Coefficient Matrix: **Bottom Decile** by Market Power

	y_{t-1}	r_{t-1}	$RELATIVE_{t-1}$	Δr_{t-1}	$Dividend : Price_{t-1}$	$TERMSPREAD_{t-1}$	MPS_t
y_t	**0.0100**	**0.000575****	**-0.00119**	**0.000338**	**-0.00135**	**0.00503*****	$\boxed{\textbf{-0.0676}^{*}}$
	(0.0227)	(0.000208)	(0.00125)	(0.00508)	(0.00108)	(0.00582)	(0.0138)
r_t	**0.249**	**0.984*****	**0.152*****	**0.701*****	**0.0228****	**0.0521*****	**0.0341*****
	(0.201)	(0.00179)	(0.0121)	(0.0442)	(0.00830)	(0.00501)	(0.0204)
$RELATIVE_t$	**0.0987**	**-0.0240*****	**0.686*****	**0.871*****	**0.0231****	**0.0711*****	**0.0387*****
	(0.207)	(0.00189)	(0.0140)	(0.0485)	(0.00883)	(0.00548)	(0.00192)
Δr_t	**-0.0553**	**-0.01127*****	**0.0822*****	**-0.207*****	**0.00803**	**0.0308*****	**0.0147*****
	(0.101)	(0.000942)	(0.00684)	(0.0249)	(0.00465)	(0.00268)	(0.00898)
$Dividend : Price_t$	**-0.155**	**0.00241**	**-0.0176**	**0.0179**	**0.00175**	**-0.00811**	**0.0189**
	(0.0969)	(0.00232)	(0.0135)	(0.0246)	(0.0254)	(0.00952)	(0.0747)
$TERMSPREAD_t$	**-0.533*****	**0.00214**	**-0.202*****	**-0.338*****	**-0.0135**	**0.930**	**-0.0198*****
	(0.209)	(0.00196)	(0.0123)	(0.0450)	(0.0110)	(0.00568)	(0.00148)

(b) VAR Coefficient Matrix: **Top Decile** by Market Power

	y_{t-1}	r_{t-1}	$RELATIVE_{t-1}$	Δr_{t-1}	$Dividend : Price_{t-1}$	$TERMSPREAD_{t-1}$	MPS_t
y_t	**0.0393****	**0.000622*****	**0.00108**	**-0.00472**	**0.000195**	**0.00451*****	$\boxed{\textbf{-0.0330}^{*}}$
	(0.0171)	(0.000159)	(0.00103)	(0.00501)	(0.000155)	(0.000392)	(0.0103)
r_t	**0.711*****	**0.973*****	**0.214*****	**0.783*****	**0.00236**	**0.0599*****	**0.0168*****
	(0.161)	(0.00146)	(0.00991)	(0.0475)	(0.00158)	(0.00347)	(0.00161)
$RELATIVE_t$	**0.466****	**-0.0334*****	**0.741*****	**0.997*****	**0.00178**	**0.0796*****	**0.0131*****
	(0.165)	(0.00153)	(0.0115)	(0.0531)	(0.00167)	(0.00373)	(0.00165)
Δr_t	**0.140***	**-0.0153*****	**0.0998*****	**-0.135*****	**0.000689**	**0.0338*****	**0.0592*****
	(0.0802)	(0.000743)	(0.00540)	(0.0255)	(0.000915)	(0.00185)	(0.00779)
$Dividend : Price_t$	**0.419**	**0.00897**	**-0.102**	**0.233**	**-0.00165**	**-0.0434**	**-0.771**
	(0.824)	(0.00780)	(0.0762)	(0.144)	(0.00142)	(0.0408)	(0.821)
$TERMSPREAD_t$	**-0.757*****	**0.0142*****	**-0.264*****	**-0.383*****	**-0.00234*****	**0.919*****	**-0.0134*****
	(0.151)	(0.00153)	(0.00901)	(0.0424)	(0.000556)	(0.00414)	(0.00103)

Table 1.10: Quarterly Bank VAR Estimates Pre-ZLB for 1984Q1-2008Q4 including Monetary Policy Surprises by Market Power

Panel (a) reports the VAR Coefficient Matrix of the bottom decile by market power for estimating Equation 1.28 using OLS pooled regressions from 1984Q1-2008Q4 for each state variable and including monetary policy surprises MPS_t as an exogenous variable. The six state variables are y_t (stock return), r_t (3 month interest rate), $RELATIVE_t$ (6 month rate minus its 12 month moving average), Δr_t (change in the 6 month rate), $Dividend : Price_t$ (dividend price ratio), and $TERMSPREAD_t$ (the difference between the 10 year rate and 3 month rate). The number in **bold** is the regression coefficient and the number in parenthesis is a robust standard error. Panel (b) reports the VAR Coefficient Matrix of the top decile by bank risk for estimating Equation 1.28. *, **, *** denote significance at the 10%, 5%, and 1% level respetively

(a) VAR Coefficient Matrix: **Bottom Decile** by Market Power

	y_{t-1}	r_{t-1}	$RELATIVE_{t-1}$	Δr_{t-1}	$Dividend : Price_{t-1}$	$TERMSPREAD_{t-1}$	MPS_t
y_t	**-0.0475*****	**-0.00911**	**0.00489****	**0.0173**	**0.0649**	**0.0507*****	$\boxed{\mathbf{0.00122}}$
	(0.0140)	(0.00560)	(0.00237)	(0.00990)	(0.0429)	(0.0302)	(0.0101)
r_t	**-0.0664*****	**0.915*****	**0.0334*****	**0.101*****	**-0.0594**	**0.446*****	**-0.212*****
	(0.0157)	(0.704)	(0.0136)	(0.0120)	(0.0407)	(0.0366)	(0.0193)
$RELATIVE_t$	**0.0275**	**-0.253*****	**0.657*****	**0.217****	**0.0205**	**0.0137*****	**-0.349*****
	(0.0180)	(0.0543)	(0.305)	(0.114)	(0.0353)	(0.00466)	(0.0226)
Δr_t	**-0.0271*****	**-0.128**	**0.0247*****	**-0.183*****	**-0.0864**	**0.0706*****	**0.151*****
	(0.00867)	(0.284)	(0.000696)	(0.0458)	(0.104)	(0.0262)	(0.0117)
$Dividend : Price_t$	**-0.109**	**0.0829**	**0.0362**	**-0.0638**	**0.00168**	**0.00458**	**-0.0544**
	(0.195)	(0.0647)	(0.0367)	(0.0754)	(0.00261)	(0.00555)	(0.115)
$TERMSPREAD_t$	**1.826*****	**0.308*****	**-0.564*****	**1.394*****	**0.00353**	**0.946*****	**1.66*****
	(0.104)	(0.0341)	(0.0757)	(0.388)	(0.230)	(0.230)	(0.703)

(b) VAR Coefficient Matrix: **Top Decile** by Market Power

	y_{t-1}	r_{t-1}	$RELATIVE_{t-1}$	Δr_{t-1}	$Dividend : Price_{t-1}$	$TERMSPREAD_{t-1}$	MPS_t
y_t	**-0.162**	**-0.0685**	**0.0145**	**0.0935**	**0.0975**	**0.0110*****	$\boxed{\mathbf{0.0564}}$
	(0.126)	(0.0461)	(0.0158)	(0.0555)	(0.0119)	(0.00273)	(0.0816)
r_t	**0.0129**	**0.934*****	**0.0403*****	**-0.0387**	**-0.0233**	**0.0286**	**-0.101**
	(0.126)	(0.0843)	(0.0128)	(0.0624)	(0.0173)	(0.0384)	(0.128)
$RELATIVE_t$	**-0.142**	**-0.215*****	**0.661*****	**0.174*****	**-0.000117**	**0.0154*****	**-0.298****
	(0.144)	(0.0608)	(0.247)	(0.0830)	(0.000186)	(0.00447)	(0.150)
Δr_t	**-0.0586**	**-0.145*****	**0.0260*****	**-0.200*****	**0.00275**	**0.00817*****	**0.130***
	(0.0571)	(0.0255)	(0.00551)	(0.0276)	(0.00899)	(0.00246)	(0.0761)
$Dividend : Price_t$	**-1.53**	**0.512**	**0.304**	**-0.587**	**-0.0332**	**0.384**	**-2.412**
	(1.597)	(0.653)	(0.315)	(0.621)	(0.0338)	(0.402)	(3.54)
$TERMSPREAD_t$	**0.649**	**-0.0767**	**-0.546*****	**1.423*****	**0.00476*****	**0.982*****	**2.02*****
	(0.658)	(0.305)	(0.0619)	(0.192)	(0.000781)	(0.174)	(0.429)

Table 1.11: Quarterly Bank VAR Estimates ZLB for 2009Q1-2016Q4 including Monetary Policy Surprises by Market Power

Panel (a) reports the VAR Coefficient Matrix of the bottom decile by market power for estimating Equation 1.28 using OLS pooled regressions from 1984Q1-2008Q4 for each state variable and including monetary policy surprises MPS_t as an exogenous variable. The six state variables are y_t (stock return), r_t (3 month interest rate), $RELATIVE_t$ (6 month rate minus its 12 month moving average), Δr_t (change in the 6 month rate), $Dividend : Price_t$ (dividend price ratio), and $TERMSPREAD_t$ (the difference between the 10 year rate and 3 month rate). The number in **bold** is the regression coefficient and the number in parenthesis is a robust standard error. Panel (b) reports the VAR Coefficient Matrix of the top decile by bank risk for estimating Equation 1.28. *, **, *** denote significance at the 10%, 5%, and 1% level respetively

Chapter 2

Credit Spreads and Monetary Policy

2.1 Introduction

Corporate bond spreads are a useful barometer to gauge overall credit conditions in the macroeconomy. The amount by which firms must pay above a risk-free rate provides insight to the overall default risk of the firm and the premium investors demand to hold these assets. Other important factors that determine this spread include the illiquidity and callability of the bond as well as preferential tax treatments given to Treasury bonds. However, interest rates, and more specifically, expectations of future rates, are the most obvious factor which will determine changes in these spreads. In this paper, I study how shocks to expectations of future interest rates affect monthly changes in corporate bond spreads and relate this sensitivity to its expected default and risk premium component. Focusing on shocks to interest rates expectations, as opposed to interest rate changes, is required in order to estimate the casual effects on credit spreads. To my knowledge, this is the first paper to study the effects of monetary policy announcement surprises on credit spreads and to decompose these effects into expected default and risk premia.

I measure these monetary policy shocks as changes in expectations of the current federal funds target as well as the path of future rates induced by Federal Open Market Committee announcements. These shocks reflect surprises of market participant's forecast of what the short term target and path of interest rates will be. I find that a 100 basis point tightening surprise reduces corporate bond spreads by 32 basis points over a month and that more than half of this effect arises due to changes in the bond's risk premium. While this negative relationship has been well documented using changes in Treasury yields (Longstaff and Schwartz (1995), Duffee (1998), and Collin-Dufresn et al. (2001)), I find that this effect continues to hold when focusing on the unexpected and exogenous change in interest rates. In order to understand this empirical relationship, I turn to different theories offered in the literature to reconcile why credit spreads narrow as a result of monetary tightenings. Rather than taking a stand on which theory is correct, I discuss how each lends credence to the negative casaul effect of monetary policy tightenings on credit spreads.

The most pervasive structural model of studying corporate debt begins with Merton (1974). Under his framework, a firms value evolves according to a drift process and default occurs when its value falls below its liability. If interest rates rise, this increases the drift of the risk-neutral process for firm value and allows assets to grow more. This then makes the risk neutral probability of default lower. A further implication of the model is that riskier firms are closer to the default threshold and therefore should face a larger sensitivity to interest rate changes. I test this implication using bond ratings as a proxy for risk and find a monotonically increased sensitivity of credit spreads as risk rises. Although I use monetary policy shocks to understand innovations in interest rates, the role of monetary policy is largely absent in Merton (1974) because the risk free rate is assumed to be fixed. Thus, the negative relationship between interest rates and credit spreads are a direct result from the assumptions imposed on the dynamics of firm value and lack further economic intuition. The next two theories of Fed information and preferred habitat fill this void by building economic intuition.

A more recent theory by Nakamura and Steinsson (2018) suggests that surprise tightenings lead to higher expectations of output growth - a result in stark contrast with traditional models of monetary contractions [1]. Under their "Fed Information" hypothesis, surprise monetary tightenings encourage market participants to become more optimistic of future economic prospects. They argue this occurs because each

[1] An earlier paper by Romer and Romer (2000) shows that the Federal Reserve has an advantage over private sector forecastors on inflation and real output. They claim this explains why longer horizon interest rates increase upon Fed tightenings

FOMC announcement conveys information about the path of the natural rate of interest. Commonly referred to as r^*, this is the interest rate that would prevail without pricing frictions and is of interest to market participants in gauging the trajectory of the macroeconomy. While their study focuses on market beliefs about higher future output growth, this implication is compatabile with a narrowing of credit spreads or easier borrowing conditions for firms. An implication of this narrative, however, is that monetary policy shocks that convey optimism for bonds should also be reflected in the stock market in the form of increased stock prices. However, Nakamura and Steinsson (2018) and I both find that stock prices decline following a monetary policy tightening shock - a result that is difficult to reconcile with improved optimism.

The decline in credit spreads as a result from tightening shocks is equivalent to Treasury yields rising far more than corporate bond yields. This differential pass-through effect of policy has been documented by Krishnamurthy and Vissing-Jorgensen (2012) as a "preferred-habitat theory" which argues that it is driven by safety attributes that investors will value depending on the supply of Treasuries. Under their narrative, during times when the supply of Treasuries or other safe assets are high, investors do not value safety and liquidity as much as they would if they were scarce. As a result, the price of Treasuries are relatively low and its yield is high relative to riskier assets which seem more attractive. Therefore, open market operations which seek to raise the interest rate by increasing the supply of Treasuries in the economy raise the yield of safe assets more than that of riskier ones which reduces credit spreads. This argument is most relevant for recent episodes of quantitative easing where the Federal Reserve purchased and reduced the supply of Treasuries in the economy but difficult to reconcile with shocks outside from quantitative easing. In the next section, I discuss related literature that has closely studied the pass-through effects of monetary policy. In Section 2.3, I introduce the data set used, Section 2.4 the empirical results, Section 2.5 the theory that support these results, and Section 2.6 concludes.

2.2 Related Literature

The safety premium theory suggests that during times of monetary tightening, Treasury yields rise above corporate bond yields because the price of Treasuries fall by more than the price of corporate bonds. This mechanism occurs because monetary tightening leads to (or the perception) of an increase in the supply of Treasuries (safe assets) and lowers the safety premium that investors value. This requires evidence that tightening (easing) corresponds to an increase (decrease) in bond supply. I discuss a number of papers which have documented this correspondence.

In a Brookings paper written before the Great Recession, Bernanke et al. (2004) reflect on three historical episodes that serve as an experiment for understanding the link between the supply of Treasuries and Treasury yields. The first episode occurred in 1999-2000 when a series of policy changes and economic forces led the US to have a budget surplus. The Treasury announced a debt buy-back program that would occur in a number of stages. It cut the issuance of Treasury bills and long term Treasury bonds and announced in August 1999 that it would consider buying back older off-the-run issues. They argued that this represented a significant supply shock because it amounted to 10% of outstanding stock of bonds and found that by bracketing each announcement days, Treasury yields fell sharply.

The second episode occurred following the Asian Financial Crisis of 1998 where the Japanese government was concerned about an appreciation of the yen against the dollar. Japan intervened by purchasing around $ 300 billion in Treasury securities. The authors offer suggestive evidence by estimating that Treasury yields fell sharply on dates around Japanese interventions. The final and third episode occurred around the summer of 2003 when the Federal Reserve was concerned with deflation. They entertained ideas of unconventional monetary policy in the form of long term Treasury purchases which drove yields down sharply. Although the FOMC never undertook these actions, this episodes points to how an allusion of purchases affected Treasury yields. This effect appears in my intradaily monetary policy shock data during the FOMC meeting on March 18, 2009, where the Federal Reserve introduced a program to purchase up to $ 300 billion of Treasury coupon securities. In their statement, they write:

> "Moreover, to help improve conditions in private credit markets, the Committee decided to purchase up to $300 billion of longer-term Treasury securities over the next six months."

This came as a huge surprise as Bloomberg on the morning of that announcement reported that Goldman Sachs and several other banks believed that they would not engage in such a program. As a result, my monetary policy shock data reports that the 10-Year on-the-run Treasury yield fell by 44bp - the most among all FOMC meetings. This offers further evidence that an announcement of an intention to reduce Treasury securities is enough to drive down Treasury yields.

A paper by DAmico and King (2013) shows that the Federal Reserve's $ 300 billion purchase of Treasuries in 2009 reduced yields by an average of about 30 basis points over the life of the program and shifted the yield curve down by 50 bp. Their results are consistent with the theory that a withdrawal of Treasury supply reduces yields. Furthermore, they find that the reduction of yields was strongest for securities that were specifically bought and those with similar maturities.

The period outside of quantitative easing episodes, however, requires a different narrative unrelated to open market operations. Vayanos and Vila (2009) offer a different story of preferred habitats that involves the demand for safe assets. Under their framework, the economy consists of investors such as pension funds who have preferences for a specific maturity of assets and risk-averse arbitrageurs who integrate markets by long-short positions on bonds. When the federal funds or short term interest rate unexpectedly rises, this becomes an attractive asset to hold relative to bonds. Because investors prefer to hold specific assets, they do not deviate from their preferred habitat. Instead, risk-averse arbitrageurs buy (long) the short rate by borrowing (short) money from the Treasury market. This drives down the price of Treasuries and thus, drives up the risk free yield without affecting that of riskier bonds.

2.3 Data

Bond Spreads

I construct the panel of corporate bond data from January 1973 to December 2016 by combining five data sources: Lehman Brothers Fixed Income Database, the Mergent FISD/NAIC Database, TRACE, DataStream, and Merrill Lynch. Among overlaps that exist in these data sets, I prioritize in the same order listed above. I remove junior bonds, bonds with floating rates and with option features other than callable bonds. It is important to note that I remove traditional callable bonds which enables the issuer to pay off remaining debt earlier[2]. In a declining interest rate environment, the incentives to call a bond will increase, thus complicating the interpretation of monetary policy effects on bond yields. However, I don't discard make-whole callable bonds in which the issuer must compensate the holder for any losses associated with calling the bond. These losses are typically determined by discounting the bond's remaining contractual cash flows at an appropriate Treasury rate. Therefore, the payoff of a make-whole callable bond option is zero and there is no economic benefit

[2] Duffee (1998) has shown that prior work relating credit spreads to interest rates did not account for the callability of bonds in their empirical analysis.

towards calling it before its maturity[3]. In addition, I apply three important filters to account for erroneous reporting by the data source. First, I remove corporate bond observations that have prices higher than a maturity matched Treasury bond. Second, I drop price bonds below one cent per dollar. Third, I remove observations that show a large bounceback in returns. Specifically, I compute the product of the adjacent return observations and remove both observations if the product is less than - 0.04. These filters lead to an unbalanced panel data of 937,418 bond month observations for 20,820 bonds over 528 months. Treasuries are matched with corporate bonds by its maturity and is attained from the Federal Reserve's constant maturity yields data[4]. Credit ratings are obtained from Standard & Poors when available, and Moodys ratings when Standard & Poors rating is unavailable.

Decomposition into Risk Premia and Expected Default

For event studies related to monetary policy, it is ideal to isolate a narrow window around an FOMC announcement to avoid the possibility of other news besides monetary policy contaminating the results. Typical windows that have been shown to be useful in the literature include intradaily, daily, and weekly changes of the dependent variable. I first estimate daily changes of credit spreads on monetary policy

[3]Elsaify and Roussanov (2016) offer a theory for the emergence of make-whole callable bonds which are always "out of the money"

[4]A common issue that plagues micro studies of credit spreads is that of duration mismatch. Prior work on constructing credit spreads simply subtracted corporate bond yields from a zero-coupon Treasury security of the same security. Under this framework, monetary policy surprises could result in smaller credit spreads simply because of a mechnical rise in the risk-free Treasury security above that of the corporate bond yield. In constructing credit spreads, however, I mitigate this problem by following Gilchrist and Zakrajšek (2012) and construct a hypothetical matching Treasury security with identical cash flows as the corporate bond. These cash flows are discounted using continuously couponded zero-coupon Treasury prices.

surprises as a benchmark result. However, because I am interested in decomposing credit spreads into a component related to risk premia and expected default, I follow the literature of Nozawa (2017) and Campbell and Shiller (1988b) and estimate a monthly vector auto-regression (VAR) with my constructed panel of bond data. The monthly event study that I subsequently estimate using these two components is required if I'm interested in understanding whether risk premium or expected default is driving the sensitivity of credit spreads to monetary policy shocks. The state vector of my VAR is :

$$X_{i,t} = \begin{pmatrix} r^e_{i,t} & d_{i,t}s_{i,t} & \tau_{i,t}PD_{i,t} & r^{EQ}_{i,t} & bm_{i,t} \end{pmatrix}' \tag{2.1}$$

which follows the dynamics:

$$X_{i,t+1} = AX_{i,t} + W_{i,t+1} \tag{2.2}$$

where $d_{i,t}$ is a vector of dummy variables for credit ratings defined as $d_{i,t} = (1 \;\; d^A_{i,t} \;\; d^{Baa}_{i,t} \;\; d^{Ba}_{i,t})$ such that $d^{\theta}_{i,t}$ is a dummy for rating θ, $\tau_{i,t}$ is the duration of bond i, $PD_{i,t}$ is its probability of default, and $r^{EQ}_{i,t}$ is the issuer's excess equity return, and $bm_{i,t}$ is its book to market ratio[5]. Utilizing an accounting identity that relates credit spreads to risk premium and expected default and imposing structure on the coefficient matrix

[5]Campbell and Shiller (1988b) pioneered this decomposition framework by relating current stock returns to the price-dividend ratio and dividend growth.

A, I am able to decompose credit spreads in the following way:

$$s_{i,t} \approx \underbrace{E\left[\sum_{j=1}^{T_i-t} \rho^{j-1} r^e_{i,t+j} \ \ |\mathcal{F}_t\right]}_{\text{Risk Premia}} + \underbrace{E\left[\sum_{j=1}^{T_i-t} \rho^{j-1} l_{i,t+j} \ \ |\mathcal{F}_t\right]}_{\text{Expected Default}} + \text{const} \tag{2.3}$$

where $\mathcal{F}_t$ is the information set of agents at time t. Equation 3.5 shows that variations in credit spreads can be decomposed into long run expected excess returns (r^e_i) or credit loss (l^t_i). I denote the risk premia component of Equation 3.5 as $s^r_{i,t}$ and the expected default component as $s^d_{i,t}$. Because exploring the properties of this decomposition is not the focus of this paper, I leave out the derivation and assumptions used in separating out risk premia and expected default from credit spreads. Instead, I invite the reader to refer to Nozawa (2017) or Appendix C.1 of my third chapter for full details on its derivation.

Monetary Policy Shocks

Monetary policy shocks, or the nonsystematic changes in policy, is required to estimate the causal effects of tightening on credit spreads. The goal of identifying a proxy for monetary policy shocks is inherently difficult because we often think of monetary policy as following a rule. If this is the case, movements in variables related to monetary policy such as the money supply or the federal funds rate is attributed to the systematic component of monetary policy rather than deviations from the rule itself. However, standard macroeconomic models typically identify shocks as deviations from a Taylor rule and there are no good theories as to what a structural monetary policy shock should be[6]. For this reason, many have attributed monetary policy shocks as either surprises the market did not expect or changes in preferences of policy makers (Owyang and Ramey (2004)). I focus on the former and follow in the direction of a large existing literature that measure monetary policy surprises as intradaily changes in the target federal funds rate around FOMC meetings. Beginning with Kuttner (2001) and extended by Gürkaynak et al. (2005) to incorporate an additional "path" surprise of monetary policy, these shocks have been shown to affect asset prices in event studies (Bernanke and Kuttner (2005))[7][8] The target surprise, denoted by $MP1$ is the unexpected change in the current month federal funds rate target. The path surprise, the residuals of regressing the fourth eurodollar futures contract $ED4$ onto $MP1$ are by construction, orthogonal to the target surprise and affect only expected future rates. The path surprise of monetary policy was introduced by Gürkaynak et al. (2005) who argued that quantifying this additional dimension better captures monetary policy. The fourth eurodollars futures contract is a bet on what the 3-month LIBOR rate will be one year ahead and contains information about the path of future policy. By considering the residuals of $ED4$ on $MP1$, I am effectively isolating information related to the stance of future policy that is not explained by the

[6]Ramey (2016) provides an excellent survey on the literature of monetary policy shocks and describes how its identification has changed over time

[7]A recent paper by Swanson (2015) features a third factor of monetary policy related to Large Scale Asset Purchases (LSAP) shocks. As a robustness check on different types of monetary policy shocks, I consider these "Swanson" shocks in my empirical analysis which can be found in Appendix B.1.

[8]A non-exhaustive list of papers that have used FOMC announcement induced shocks to interest rate futures include Gertler and Karadi (2015), Ottonello and Winberry (2018), Nakamura and Steinsson (2018), and English et al. (2018b).

current policy surprise. This approach, differs however from Gürkaynak et al. (2005), who apply principal components analysis to extract two factors and apply a rotation and normalization to derive the target and path shocks. While my approach does not use as much information on the term structure, it allows me to avoid a two-step estimation and adjust my standard errors of generated regressors[9]. Finally, by choosing to focus on a narrow window around FOMC announcements (2PM EST), I am capturing news only related to monetary policy and not other developments in the macroeconomy. More importantly, the changes that I am capturing are also exogenous monetary policy surprises because the central bank is not responding concurrently to asset price reactions generated by its announcement. This is important in properly identifying exogenous changes in policy and largely unaccounted for by previous papers which have used monthly interest rate changes. Details on the construction of these monetary policy shocks can be found in Appendix C.2.2 of my third chapter.

2.4 Empirical Analysis

The choice between using smaller and longer windows around FOMC meetings in event studies is a clear one. If I hope to capture surprise changes in interest rate expectations driven by monetary policy and uncontaminated by other news,

[9]Gilchrist et al. (2015) uses a similar methodology except they regress the 10-Year Treasury yield on the 2-Year Treasury yield

I should use a smaller interval around the meeting. A central goal in the paper, however, is not only to understand how tightening surprises affect credit spreads, but also to decompose this effect into expected default and risk premia. This requires a decomposition using a VAR and therefore monthly data on credit spreads. The tradeoff towards using monthly data to study this decomposition is the potential of contaminating the event study with other information released during the month. In order to motivate the empirical relationship between the shocks and spreads, I begin my analysis using daily data and move towards monthly data in subsequent sections. I show that the negative relationship between tightening shocks and credit spreads holds both in the daily and monthly event study regressions.

2.4.1 Daily Results

I use data from Merrill Lynch and compute a face-value weighted average across all bonds to create a daily time series of bond spreads from January 2, 1997 to December 31, 2016. I then estimate the following regression:

$$\Delta SPREAD_t = \beta_0 + \beta_1 MP1_t + \beta_2 PATH_t + \epsilon_t \tag{2.4}$$

where Δ is computed as a one-day change in the spread around FOMC announcement date t[10]. Monetary policy surprises are defined with two intradaily components on

[10] If the FOMC announcement occurs on date t, Δ is computed as the difference between t and $t-1$

date t: (i) the surprise in the current month federal funds rate target ($MP1$) and (ii) the residuals from a regression of the fourth eurodollars futures ($ED4$) contract onto $MP1$, which I denote as $PATH$. Table 2.1a reports the results and shows that a 100 basis point path surprise leads to a 15 basis point decline in credit spreads during the full sample (Column 1), a 12 basis point decline in the pre-ZLB (Column 2), and a 45 basis point decline during the ZLB (Column 3). Tightening surprises as proxied by changes in the current month target rate $MP1$ does not yield statistically significant results. Therefore, the results suggest that the negative relationship between tightening surprises and credit spreads at the daily frequency is driven by surprises to the path of policy - an implication that Swanson (2017) also finds.

Using daily data, however, raises issues of "stale" prices in which the spreads reported on day t could have been agreed upon a few days in advance ($t-1$ or $t-2$). Since corporate bonds trade infrequently, the use of "stale" prices in my event study could underestimate the impact of policy shocks on credit spreads. This could be mitigated by either using a multi-day event window in order to properly capture actual movements in bond prices, or by using data that is recorded on a transactions basis. Because the former could potentially introduce additional news that occurs during the expanded event window besides monetary policy, I address the concern of "stale" prices by using TRACE data which are reported on a transaction time basis. In other words, when two parties agree on a bond price on date t, this will be accurately reflected on the data entry of date t as a transactions price. Using TRACE would mitigate concerns of stale prices. The results using TRACE transactions based data is presented in Table 3.7b and shows the same negative coefficient as using Merrill Lynch data except with a larger magnitude. This larger magnitude confirms the potential of stale pricing that occurs in Panel 2.1a. I find that tightening surprises as proxied by $PATH$ result in a decline of about 43 basis points in the full and pre-ZLB sample and 63 basis points in the ZLB sample.

The decline of credit spreads due to monetary tightening shocks has been documented by a number of papers in the literature. More specifically, Arai (2017), Raskin (2014), and Swanson (2017) all seem to find a stronger pass-through of policy shocks to safe bond yields. Because of differences in our definition of spreads, shocks, and time periods, these papers do not perfectly align with mine. In terms of identifying policy shocks, the paper closest to mine is Swanson (2017), although both the definition of spreads and shocks are different. In his paper, he focuses on the spread between Moody's Aaa and the 10-Year Treasury yield and measures shocks along three dimensions: target rate, forward guidance, and large scale asset purchases[11].

[11] I describe the construction of these shocks in Appendix B.1.

(a) Merrill Lynch Data

	(1) Full Sample 1997-2016	(2) Pre-ZLB 1997-2008	(3) ZLB 2009-2016
MP1	0.00129	-0.00218	
	(0.0697)	(0.0721)	
PATH	-0.149***	-0.120**	-0.448***
	(0.0541)	(0.0572)	(0.140)
Constant	-0.000561	-0.00138	0.00117
	(0.00401)	(0.00558)	(0.00443)
Observations	167	111	56
R^2	0.0512	0.0373	0.228

(b) TRACE Data

	(1) Full Sample 1997-2016	(2) Pre-ZLB 1997-2008	(3) ZLB 2009-2016
MP1	-0.562	-0.505	
	(0.374)	(0.351)	
PATH	-0.432***	-0.433**	-0.629*
	(0.164)	(0.175)	(0.326)
Constant	-0.0166	-0.0400**	0.00990
	(0.0118)	(0.0172)	(0.0154)
Observations	125	65	60
R^2	0.108	0.154	0.0435

Table 2.1: Daily Changes in Credit Spreads Time Series Regression
February 5, 1997 - December 14, 2016

This table reports results from estimating Equation 2.4 of a regression of daily changes in credit spreads on monetary policy shocks $MP1$ and $PATH$. The changes are taken around a one day window of each FOMC meeting. In Panel 2.1a the data-source is Merrill Lynch and in Panel 3.7b the data source is from TRACE. Column (1) presents results for the full sample (1997-2016), Column (2) results for the Pre-ZLB (1997-2008), and Column (3) results for the ZLB (2009-2016). Standard errors are robust White standard errors.

I apply the same shocks that I use in Table 2.1 on the credit spread sample considered from Swanson (2017) and report the results in Table 2.2. There are several differences between our methodology that are worth noting. First, while I use $MP1$ as a proxy for the surprise changes in the federal funds rate target, Swanson (2017) applies principle component analysis to strip out the component related to the target. Second, our shocks to forward guidance differ as I use the residuals from the projection of $ED4$ onto $MP1$ as the proxy and he again uses the second principle component as its proxy. Third, he includes an additional dimension of large scale asset purchases (LSAPS) as a shock only related to quantitative easing and finds that it is highly significant during the ZLB even while controlling for forward guidance. These differences in monetary policy shocks arise by how we interpret the pass-through effects of monetary policy. Whereas Swanson (2017) measures the impact on credit spreads for one standard deviation higher level of each factor of policy, I measure the response to a 100 basis point surprise in the target ($MP1$) and $PATH$. In other words, my coefficients are interpreted as how much of the 1% tightening surprise is transmitted to credit spreads. Nonetheless, the analysis relating my measure of monetary policy shocks with the Moody's credit spread used by Swanson (2017) is important to understand whether there are large differences when using different proxies for shocks.

In Table 2.2, I find that tightening surprises as proxied by both the target rate ($MP1$) and forward guidance ($PATH$) correspond to a decline in credit spreads. While it is difficult to compare the magnitudes of the coefficient with Swanson (2017) because of differences of how the shocks are defined, the decline is similar along two dimensions. First, the $PATH$ surprise has a larger negative effect on credit spreads than $MP1$. Second, in comparing the pre-ZLB with the ZLB period, both Swanson (2017) and I find that the effect is stronger in the ZLB period. The stronger negative effect in the ZLB period corresponds to corporate bond yields responding less than Treasury yields. This attenuated pass-through effect of corporate bond yields during the ZLB has been documented by Kiley (2016) who measures shocks as surprises in 5-year, 10-year, and 30-year Treasury yields. Examining the reason for this time varying effect is outside the scope of this paper and requires a structural model to disentangle channels related to duration, liquidity, and safety over time. There is a concern that the negative relationship in Table 2.2 is entirely mechanical because I am simply subtracting the 10-Year Treasury yield from corporate bond yields without carefully matching its duration. The results in Table 2.1, however, addresses this concern by creating a cashflow matched synthetic Treasury as in Gilchrist and Zakrajšek (2012). Nonetheless, my results in Table 2.1 also reveals a similar attenuation in the pass-through effect during the ZLB.

In terms of interpreting coefficients as the level of monetary policy pass-through, a closely related paper is Raskin (2014) who uses an identification by heteroskedasticity by exploiting differences in the variance of policy shocks on days of FOMC announcements compared with non-FOMC days. While he does not directly study the effects on credit spreads, he finds a greater pass-through effect on corporate bond yields of safe AAA bonds relative to riskier BBB bonds which suggests a narrowing of spreads between the two groups upon tightening. Arai (2017) applies the same identification strategy to Japanese corporate bonds and finds a similar one to one pass through for high grade corporate bond yields during Bank of Japan announcement dates. Using unexpected changes in 2 and 10 Year Treasury yield, Gilchrist et al. (2015) finds evidence of a complete pass-through effect on most corporate bond and Treasury yields leaving credit spreads largely unchanged. One notable exception, however, is that they find a limited pass through effect, and therefore a decline of credit spreads for BBB bonds during the ZLB period. They attribute this differential behavior as reflecting poor liquidity during the financial crisis of 2008 which further deteriorated the functioning of asset markets.

(a) Moody's AAA minus 10-Year Treasury

	(1) Full Sample 1988-2018	(2) Pre-ZLB 1988-2008	(3) ZLB 2009-2015	(4) Lift-Off 2016-2018
MP1	-0.159**	-0.166**		
	(0.0794)	(0.0785)		
PATH	-0.242***	-0.200***	-0.657**	-0.564***
	(0.0596)	(0.0569)	(0.237)	(0.128)
Constant	0.00355	0.00129	0.00966	0.00333
	(0.00261)	(0.00280)	(0.00780)	(0.00641)
Observations	272	197	48	27
R^2	0.187	0.201	0.239	0.458

(b) Moody's BAA minus 10-Year Treasury

	(1) Full Sample 1988-2018	(2) Pre-ZLB 1988-2008	(3) ZLB 2009-2015	(4) Lift-Off 2016-2018
MP1	-0.156**	-0.158**		
	(0.0742)	(0.0730)		
PATH	-0.263***	-0.220***	-0.726***	-0.570***
	(0.0616)	(0.0586)	(0.237)	(0.121)
Constant	0.00386	0.00287	0.00526	0.00328
	(0.00246)	(0.00278)	(0.00635)	(0.00612)
Observations	272	197	48	27
R^2	0.226	0.225	0.358	0.509

Table 2.2: Daily Changes in Credit Spreads Time Series Regression using Moody's Indices
November 2, 1988 - May 2, 2018

This table reports results from estimating Equation 2.4 of a regression of daily changes in credit spreads on monetary policy shocks $MP1$ and $PATH$. The changes are taken around a one day window of each FOMC meeting. In Panel 2.1a the left-hand side variable are daily changes in Moody's AAA minus 10-Year Treasury and in Panel 3.7b it is Moody's BAA minus 10-Year Treasury. Column (1) presents results for the full sample (1997-2016), Column (2) results for the Pre-ZLB (1997-2008), Column (3) results for the ZLB (2009-2015), and Column (4) results for the period known as "lift-off" (2016-2018). Standard errors are robust White standard errors.

2.4.2 Monthly Results

Having shown that tightening surprises are associated with a decline in credit spreads at the daily frequency, I now turn to event studies using monthly data. Although using monthly data in event studies can introduce news other than monetary policy, it is necessary in order to separate credit spread sensitivity into its risk premium and expected default components. Given that monetary policy shocks occur at the daily frequency on FOMC meeting dates, while credit spreads are monthly, I need to carefully match the shocks with the spreads. In order to match this daily shock variable with monthly credit spreads, I sum up all the shocks in a particular month and denote that as shocks during month t[12]. Let $SPREAD_{b,i,t}$ be the spread of bond b issued by firm i at the end of month t. The two components of expected default and risk premium are denoted by $s^d_{b,i,t}$ and $s^r_{b,i,t}$ respectively. I first take an average across all bonds b for each firm i at the end of month t to get $SPREAD_{i,t}$, $s^d_{i,t}$, and $s^r_{i,t}$. Next, I take an average across all firms at the end of month t to generate a monthly time series $SPREAD_t$, s^d_t, and s^r_t. Finally, I compute monthly changes from the end of month t to the end of month $t+1$ and denote this as $\Delta SPREAD_{t+1}$, Δs^d_{t+1}, and Δs^r_{t+1}.

[12]There are a number of ways of aggregating high frequency FOMC shocks to a lower frequency. Gertler and Karadi (2015) creates a cumulative daily shock and takes an average across all days of the month. Ottonello and Winberry (2018) aggregates to the quarterly level by taking a simple sum which is what I do

2.4.3 Empirical Results using All Bonds

I first consider the following regression using bonds of all rating and maturity:

$$\begin{aligned} \Delta SPREAD_{t+1} &= \beta_0^s + \beta_1^s MP1_{t+1} + \beta_2^s PATH_{t+1} + \epsilon_{t+1}^s \\ \Delta s_{t+1}^d &= \beta_0^d + \beta_1^d MP1_{t+1} + \beta_2^d PATH_{t+1} + \epsilon_{t+1}^d \\ \Delta s_{t+1}^r &= \beta_0^r + \beta_1^r MP1_{t+1} + \beta_2^r PATH_{t+1} + \epsilon_{t+1}^r \end{aligned} \tag{2.5}$$

where $MP1_{t+1}$ and $PATH_{t+1}$ are summed across all days in month $t+1$. This empirical specification make the timing of the shocks sensible. For example, $\Delta SPREAD_{t+1}$ could be the change in average credit spreads from the end of February to the end of March, while $MP1_{t+1}$ and $PATH_{t+1}$ are the aggregate monetary policy surprises in the month of March. Therefore, β_1 and β_2 are properly capturing the effects of target rate and path shocks respectively over the month of March. Unlike most of the prior literature which used samples before the Financial Crisis, I separate my analysis into the *full sample* (November 1988-December 2016), the *pre zero lower bound* (pre-ZLB) period (November 1988-December 2008) and the *zero lower bound* (ZLB) period (January 2009 - December 2016).

The results for the full sample, pre-ZLB, and ZLB period are reported below in Table 2.3a, Table 2.3b, and Table 2.3c respectively. For the full sample, the results suggest that a 100 basis point surprise tightening decreases monthly credit spreads by 32 basis points, expected default by 6.5 basis points and risk premium by 22 basis points. The effects seem to be particularly driven by the pre-ZLB period (Table 2.3b) and are insignificant during the ZLB (Table 2.3c). Credit spreads and its components are particularly affected by $MP1$, the surprise component in changes of the federal funds rate target, and not $PATH$, the residuals of $ED4$ that are orthogonal to $MP1$[13]

Similar to the daily results in Table 2.2, the monthly event study suggests that tightening surprises as proxied by the target shock $MP1$ leads to a statistically significant decline in credit spreads. There are, however, several differences between the daily and monthly event study. First, the standard errors in Table 2.3 are much larger which comes from the fact that a wider window period introduces the possibility that other non-monetary policy news is driving credit spreads. Second, while the $PATH$ surprise is particularly informative in driving credit spreads at the daily frequency, the target shock $MP1$ is the primary factor driving monthly changes in credit spreads. Most event studies such as Gilchrist et al. (2015) and Swanson (2017) find that at the daily frequency, the path surprise plays an important role in determining credit spreads. By aggregating path shocks, I am perhaps losing information that is otherwise informative about the future stance of monetary policy. This is particularly problematic in the zero-lower bound period (Panel 2.3c) where the coefficient on the path surprise is positive and insignificant. During the zero lower bound

[13]Swanson (2017) estimates a similar model using daily changes in the Aaa-10yr and Baa-10yr spread. He finds an insignificant decline of 0.41 basis point decline for one standard deviation of monetary policy surprise using shocks to the federal funds rate and a 0.60 basis point decline using shocks to forward guidance.

period, monthly changes in credit spreads do not seem to be driven by monetary policy shocks. There is an abundance of evidence that the zero lower bound period was marked by unconventional purchases of Treasury securities which drove down the yields of safe assets relative to riskier assets.

Because I am able to capture this using daily changes from properly matched Treasury securities with corporate yields (Table 2.1) as well as those from more conventional Moody's indexes (Table 2.2), it is likely that the monthly event study regressions are too noisy for inference during the crisis period. The zero lower bound period was also marked by significant developments in financial markets such as the bailout of Bear Stears and the demise of Lehman Brothers which undoubtedly affected credit spreads outside of FOMC meetings.

(a) Full Sample Time Series Regression November 1988 - December 2016

	(1) Spread	(2) Expected Default	(3) Risk Premium
MP1	-0.316***	-0.0650***	-0.218***
	(0.101)	(0.0245)	(0.0652)
PATH	0.127	0.0542	0.0451
	(0.241)	(0.0678)	(0.117)
R^2	0.034	0.033	0.040
Observations	170	170	170

(b) Pre-ZLB Time Series Regression November 1988 - December 2008

	(1) Spread	(2) Expected Default	(3) Risk Premium
MP1	-0.312***	-0.0646***	-0.217***
	(0.102)	(0.0249)	(0.0659)
PATH	0.116	0.0527	0.0355
	(0.249)	(0.0698)	(0.121)
R^2	0.036	0.035	0.042
Observations	138	138	138

(c) ZLB Time Series Regression January 2009 - December 2016

	(1) Spread	(2) Expected Default	(3) Risk Premium
PATH	0.542	0.113	0.415
	(0.697)	(0.168)	(0.389)
R^2	0.026	0.018	0.048
Observations	32	32	32

Table 2.3: Monthly Changes in Credit Spreads (and two components) Time Series Regression

This table reports results from estimating Equation 2.5 where s^d and s^r is expected default and risk premium respectively. Column (1) reports the results for monthly changes of credit spreads, Column (2) for monthly changes in expected default, and Column (3) for monthly changes in risk premium. Panel 2.3a presents the full sample from November 1988-December 2016, Panel 2.3b presents the pre-ZLB sample from November 1988-December 2008, and Panel 2.3c presents the ZLB sample from January 2009-December 2016. Standard errors are robust White standard errors.

2.4.4 Empirical Results using Bond Portfolios by Risk

The previous section considered all bonds together without controlling for any bond characteristics. There is evidence that the pass-through effect of monetary policy differs across firm risk (Krishnamurthy and Vissing-Jorgensen (2012), Ottonello and Winberry (2018), Collin-Dufresn et al. (2001), and Raskin (2014)). I control for bond risk by constructing bond portfolios across different ratings groups g. As in the full sample, I first take an average across all bonds b for each firm i at the end of month t to get $SPREAD_{i,t,g}$, $s^d_{i,t,g}$, and $s^r_{i,t,g}$. However, these bonds are now subscripted by a risk group g, where $g \in \{$Aa+, A, Baa, HY$\}$. I construct four bond portfolios, one for each g by taking an average across all firms in group g at the end of month t. The four portfolios from safest to riskiest are $SPREAD^{Aa+}_t$, $SPREAD^{A}_t$, $SPREAD^{Baa}_t$, and $SPREAD^{HY}_t$. I then compute monthly changes from the end of month t to the end of month $t+1$ and regress these changes on the sum of monetary policy shocks in month $t+1$.

$$\begin{aligned} \Delta SPREAD^g_{t+1} &= \beta^s_0 + \beta^s_1 MP1_{t+1} + \beta^s_2 PATH_{t+1} + \epsilon^s_{t+1} \\ \Delta s^d_{g,t+1} &= \beta^d_0 + \beta^d_1 MP1_{t+1} + \beta^d_2 PATH_{t+1} + \epsilon^d_{t+1} \\ \Delta s^r_{g,t+1} &= \beta^r_0 + \beta^r_1 MP1_{t+1} + \beta^r_2 PATH_{t+1} + \epsilon^r_{t+1} \end{aligned} \tag{2.6}$$

for $g \in \{$Aa+, A, Baa, HY$\}$.

The results for monthly changes in credit spreads, expected default, and expected excess returns using the full sample are presented in Table 2.4, 2.5, and 2.6 respectively. Similar to the results using all bonds, the effect on credit spreads is primarily driven by shocks to the target rate $MP1$. Furthermore, there is a larger decline in credit spreads for bonds that are higher risk (Column 4) compared with the safest bonds (Column 1). More specifically, a 100 basis point shock to the target rate leads to a decline of 44 basis points for the high risk bond portfolio and a 23 basis point decline for the Aa+ portfolio. The differences in sensitivity between the riskiest bonds (Column (4)) and safest bonds (Column (1)), however, is statistically insignificant. This is determined by estimating the coefficients jointly as a system and computing a χ^2 statistic for the hypothesis that β_1, the coefficient on $MP1$ is different between safe bonds and high yield risky bonds. The fact that the differences in sensitivity are not statistically significant can arise from the noisy measure of credit spreads when aggregating at the monthly level. Given that a one-day interval should better capture heterogeneities of sensitivity, a more direct test of a differential pass-through effect of monetary policy is to first take the difference between high yield spreads and safe investment grade spreads ($Y = SPREAD^{HY} - SPREAD^{Aa+}$). This difference is effectively the additional compensation that investors in riskier bonds require over investment grade bonds. I can then take changes in Y over the one-day horizon and regress it on monetary policy surprises. If it is the case that riskier bonds face a larger decline in credit spreads, we should expect this coefficient to be negative. The results of this regression is presented in Table 2.7 and shows that tightening surprises as proxied by $PATH$ lead to a greater decline in credit spreads for riskier firms relative to safer firms. The statistically significant results provides evidence that by focusing on daily changes, as opposed to the monthly changes, I am better able to capture differences in credit spread sensitivity between safe and risky firms.

The results in this section provide support that the sensitivity of bond yields to monetary policy shocks depend on the riskiness of a firm. While it is not statistically significant using monthly credit spreads, it appears strongly in the results from daily regressions. Riskier bond yields do not respond as much as safer bond yields when shocks occur, which suggests a differential pass-through effect of monetary policy. In fact, the narrowing credit spreads from tightening shocks support this notion, as the safe yield rises above any increases in the corporate bond yield. In the next section, I discuss various theories that support this notion.

(a) Full Sample Time Series Regression ($\Delta SPREAD^{g}_{t+1}$)
November 1988 - December 2016

	(1) Aa+	(2) A	(3) Baa	(4) HY
MP1	-0.234**	-0.384***	-0.383***	-0.438***
	(0.0925)	(0.0950)	(0.0891)	(0.143)
PATH	-0.0103	-0.000874	-0.0334	-0.358
	(0.0940)	(0.117)	(0.125)	(0.226)
R^2	0.017	0.045	0.040	0.043
Observations	283	280	280	280

(b) Full Sample Time Series Regression ($\Delta s^{d}_{g,t+1}$)
November 1988 - December 2016

	(1) Aa+	(2) A	(3) Baa	(4) HY
MP1	-0.0456**	-0.0742***	-0.0987***	-0.0946***
	(0.0196)	(0.0190)	(0.0246)	(0.0336)
PATH	0.00540	0.00924	-0.00123	-0.0781
	(0.0202)	(0.0245)	(0.0335)	(0.0512)
R^2	0.015	0.040	0.035	0.035
Observations	283	280	280	280

(c) Full Sample Time Series Regression ($\Delta s^{r}_{g,t+1}$)
November 1988 - December 2016

	(1) Aa+	(2) A	(3) Baa	(4) HY
MP1	-0.187***	-0.306***	-0.255***	-0.212***
	(0.0715)	(0.0745)	(0.0609)	(0.0649)
PATH	-0.0188	-0.0179	-0.0261	-0.160
	(0.0712)	(0.0893)	(0.0811)	(0.101)
R^2	0.018	0.047	0.040	0.044
Observations	283	280	280	280

Table 2.4: Monthly Changes in Credit Spreads (and two components) Time Series Regression by Risk (Full Sample)

This table reports results from estimating Equation 2.6 which regresses monthly credit spreads, expected default, and risk premium on $MP1$ and $PATH$. Panel 2.4a contains results for monthly changes in credit spreads, Panel 2.4b for changes in expected default, and Panel 2.4c for risk premium. For each of the three panels, Column (1) reports the results for bond portfolios consisting of Aa+ bonds, Column (2) for A bonds, Column (3) for Baa, and Column (4) for the riskiest HY bonds. The full sample from November 1988-December 2016 is considered. Standard errors are robust White standard errors.

(a) Pre-ZLB Time Series Regression ($\Delta SPREAD^g_{t+1}$)
November 1988 - December 2008

	(1) Aa+	(2) A	(3) Baa	(4) HY
MP1	-0.223**	-0.377***	-0.379***	-0.422***
	(0.0930)	(0.0950)	(0.0894)	(0.141)
PATH	0.00477	0.00161	-0.0286	-0.395
	(0.0981)	(0.123)	(0.132)	(0.240)
R^2	0.019	0.052	0.046	0.058
Observations	219	216	216	216

(b) Pre-ZLB Time Series Regression ($\Delta s^d_{g,t+1}$)
November 1988 - December 2008

	(1) Aa+	(2) A	(3) Baa	(4) HY
MP1	-0.0428**	-0.0728***	-0.0985***	-0.0909***
	(0.0197)	(0.0190)	(0.0248)	(0.0335)
PATH	0.00911	0.0104	0.000911	-0.0886
	(0.0211)	(0.0258)	(0.0357)	(0.0541)
R^2	0.016	0.046	0.040	0.047
Observations	219	216	216	216

(c) Pre-ZLB Time Series Regression ($\Delta s^r_{g,t+1}$)
November 1988 - December 2008

	(1) Aa+	(2) A	(3) Baa	(4) HY
MP1	-0.178**	-0.301***	-0.252***	-0.202***
	(0.0719)	(0.0746)	(0.0611)	(0.0644)
PATH	-0.00548	-0.0132	-0.0223	-0.177*
	(0.0743)	(0.0937)	(0.0856)	(0.107)
R^2	0.019	0.055	0.046	0.057
Observations	219	216	216	216

Table 2.5: Monthly Changes in Credit Spreads (and two components) Time Series Regression (Pre-ZLB)

This table reports results from estimating Equation 2.6 which regresses monthly credit spreads, expected default, and risk premium on $MP1$ and $PATH$. Panel 2.5a contains results for monthly changes in credit spreads, Panel 2.5b for changes in expected default, and Panel 2.5c for risk premium. For each of the three panels, Column (1) reports the results for bond portfolios consisting of Aa+ bonds, Column (2) for A bonds, Column (3) for Baa, and Column (4) for the riskiest HY bonds. The pre-ZLB sample from November 1988-December 2008 is considered. Standard errors are robust White standard errors.

(a) ZLB Time Series Regression ($\Delta SPREAD^{g}_{t+1}$)
January 2009 - December 2016

	(1)	(2)	(3)	(4)
	Aa+	A	Baa	HY
PATH	-0.298	-0.111	-0.184	-0.0906
	(0.337)	(0.405)	(0.394)	(0.679)
R^2	0.016	0.002	0.005	0.000
Observations	64	64	64	64

(b) ZLB Time Series Regression ($\Delta s^{d}_{g,t+1}$)
January 2009 - December 2016

	(1)	(2)	(3)	(4)
	Aa+	A	Baa	HY
PATH	-0.0630	-0.0184	-0.0485	0.00541
	(0.0753)	(0.0849)	(0.101)	(0.148)
R^2	0.016	0.001	0.005	0.000
Observations	64	64	64	64

(c) ZLB Time Series Regression ($\Delta s^{r}_{g,t+1}$)
January 2009 - December 2016

	(1)	(2)	(3)	(4)
	Aa+	A	Baa	HY
PATH	-0.267	-0.135	-0.136	-0.0439
	(0.258)	(0.322)	(0.276)	(0.299)
R^2	0.021	0.004	0.006	0.000
Observations	64	64	64	64

Table 2.6: Monthly Changes in Credit Spreads (and two components) Time Series Regression (ZLB)

This table reports results from estimating Equation 2.6 which regresses monthly credit spreads, expected default, and risk premium on $PATH$. Panel 2.6a contains results for monthly changes in credit spreads, Panel 2.6b for changes in expected default, and Panel 2.6c for risk premium. For each of the three panels, Column (1) reports the results for bond portfolios consisting of Aa+ bonds, Column (2) for A bonds, Column (3) for Baa, and Column (4) for the riskiest HY bonds. The ZLB sample from January 2009 - December 2016 is considered. Standard errors are robust White standard errors.

	(1) $\Delta SPREAD^{HY-AA+}_{1-Day}$ Full Sample (1997-2016)	(2) $\Delta SPREAD^{HY-AA+}_{1-Day}$ Pre-ZLB (1997-2008)	(3) $\Delta SPREAD^{HY-AA+}_{1-Day}$ ZLB (2009-2016)
MP1	0.0211	0.0257	-0.443
	(0.0991)	(0.108)	(0.604)
PATH	-0.413***	-0.335***	-0.842***
	(0.0861)	(0.0857)	(0.235)
Constant	-0.00180	0.00429	-0.0150
	(0.00730)	(0.0102)	(0.00949)
Observations	167	103	64
R^2	0.112	0.0902	0.251

Table 2.7: Regression of Changes in $SPREAD^{HY} - SPREAD^{Aa+}$

This table reports results from a time series regression of one day changes between the difference of high yield (HY) risky bonds and safe (Aa+) investment grade bonds on intradaily monetary policy surprises $MP1$ and $PATH$. Callable bonds and financial firms (`SIC:` 6000-7000) are removed. The time series is computed as a face-value weighted average across all bonds on a particular day. Column (1) reports results for the full sample from February 1984 - December 2016, Column (2) for the Pre-ZLB period from February 1984 - December 2008, and Column (3) for the ZLB period from January 2009 - December 2016. Standard errors are robust White standard errors.

2.5 Discussion

The standard theory of the monetary policy transmission mechanism teaches us that the yield on a private security is equal to the corresponding government yield up to a first order (Gertler and Karadi (2015)). The paradigm for New-Keynesian models is that under sticky prices, the central bank has control over the short term real rate and can effectively manipulate aggregate spending by seamlessly passing through this rate to corporate borrowing rates. Under the credit channel of Bernanke and Gertler (1995), however, higher interest rates not only raises the government yield, but also the external finance premium, making overall borrowing conditions tighter. From this perspective of contractionary monetary policy leading to lower output growth, the negative empirical relationship that I document between tightening shocks and credit spreads is surprising. If tightening shocks are associated with shocks to the stance of monetary policy unrelated to macroeconomic conditions, one would expect a positive relationship between tighter policy and credit spreads. This is because a contractionary shock in the form of higher interest rates, should all else equal, contract macroeconomic variables by making borrowing more expensive and therefore tighten credit conditions. The financial accelerator model of Bernanke et al. (1999) would also suggest that higher interest rates have an additional channel where it reduce asset prices and therefore, the overall net worth of borrowers. This additional channel could have an amplification effect by making borrowers less likely to repay loans and further increase credit spreads. However, the negative relationship between credit spreads and tightening surprises can nonetheless be reconciled with a number of theories. I discuss some of the theories which can rationalize my empirical results and address its merits and shortcomings.

Structural models of debt begin with Merton (1974) who relates a firm's credit risk to its capital structure (assets and liabilities). While the model implies a negative relationship between interest rates and credit spreads, the mechanism is largely mechanical and lacks economic intuition. Figure 2.1 plots the expected default and risk premium component of credit spreads as a function of the risk-free rate. The figure is generated using the basic model of Merton (1974) and extended by Chen et al. (2008) to allow for a separation of credit spreads into its expected default and risk premia component[14]. This occurs if we associate the expected default component with the natural (p) probability of default and the risk premia component with the risk neutral (q) probability. As we can see from Figure 2.1, the slopes are steeper for riskier bonds - that is tightening surprises have a larger effect on riskier firms - a result in line with the monthly regression results in Table 2.4a and the daily results in Table 2.7[15]. In this classical model, firm value is modeled as a Geometric Brownian motion where the risk-free rate is its drift parameter. An increase in the risk free rate increases this drift parameter which elevates firm value over time. A higher firm value leads to lower default under both the natural (p) and risk neutral (q) probability which decreases expected default and risk premium, respectively. Although the model agrees with the empirical results I find, the mechanism is largely a byproduct of the model's assumptions. The model is silent about whether expected default or risk premia is driving the sensitivity of credit spreads. I now turn to other theories which offer more economic motivation.

[14]Details on this decomposition can be found in the Appendix A of Chen et al. (2008) as well as Appendix B.3 in this chapter.

[15]Firm risk is defined by the amount of leverage. I take values from Table 2 of Huang and Huang (2012) who empirically measure firm leverage ratio across different bond ratings.

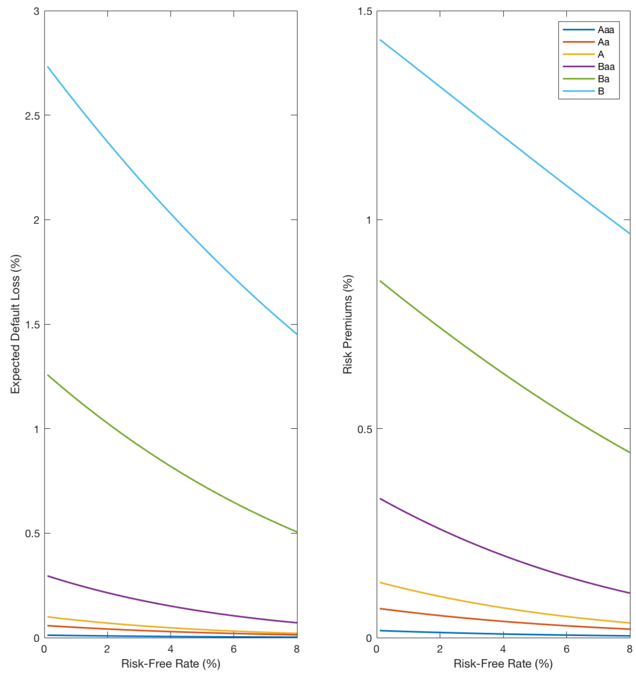


Figure 2.1: Comparative Statics of Merton (1974)

This figure plots the relationship between expected default (left figure) and risk premium (right figure) and the risk-free rate that is implied by Merton (1974). Values of leverage that are used in this figure are taken from Huang and Huang (2012). The original model by Merton (1974) does not separate credit spreads into components. In order to decompose these responses, I follow Chen et al. (2008) who relate the expected default component to the natural probability of default and risk premium to the risk-neutral probability of default. Details on this decomposition can be found in the Appendix A of Chen et al. (2008) as well as Appendix B.3 in this chapter.

What are the economic implications of the negative relationship between credit spreads and tightening surprises? The Federal Reserve's surprise increase in interest rates lead to lower borrowing costs for firms relative to the risk free rate. As mentioned, conventional theory would suggest the opposite effect and that tightening by the central bank is used to lower output, curb inflation, and tighten credit conditions. A recent theory proposed by Nakamura and Steinsson (2018) challenges this conventional narrative by describing surprise increases in interest rates as "good" news. Under their *Fed Information Effect* theory, FOMC announcements convey information not only about tightening of rates relative to the natural rate, but also an increase in the natural rate itself. An increase in the natural rate itself suggests to the market that the economy is doing well and a higher trajectory of growth should be expected[16]. By raising interest rates by more than what was expected, the Federal Reserve is communicating an optimistic path of the economy which potentially leads the market to reassess its prior beliefs. If this channel is present, one would expect credit spreads to decline. Nakamura and Steinsson (2018) regress monthly changes in survey expectations about output growth on a policy news shock and finds a positive coefficient over four different sample periods. In a similar study, Campbell et al. (2012) find that a positive shock to the federal funds rate is associated with a decrease in unemployment forecasts. They explain this phenomenon as evidence that professional forecasters interpret tightening shocks as an indicator for a stronger economy. My monthly regression results in Table 2.3, Table 2.4, and Table 2.5 show that the decline in credit spreads is almost entirely driven by the reduction in risk premia rather than expected default. The risk premium component is defined as the compensation to investors over and above lossess associated with firm default and reflects additional perceptions of risk and uncertainty of holding the bond. The massive decline in this risk premium component relative to expected default as a result of

[16]Nakamura and Steinsson (2018) estimate a structural model by incorporating Fed Information effects and find that two-thirds of the monetary policy shock are shocks to beliefs about the future natural rate.

monetary tightening suggests that investors are less fearful of uncertainty in the bond market and require less compensation to risk which is consistent with the Federal Reserve revealing a positive outlook. The marginal decline in expected default suggests that the overall probability that firms miss coupon payments or file for bankruptcy is unaffected.

However, the *Fed Information Effect* theory raise a number of inconsistencies when examined under how this optimistic information propogates to other assets such as stocks. The value of a firm is split between bondholders and stockholders who each have a claim on the firm's value. If monetary policy shocks affect firm value, this should affect corporate bond and stock values in the same direction. Under the Nakamura and Steinsson (2018) paradigm, good news revealed by the Federal Reserve is good news for both stockholders and bondholders. I test this hypothesis by computing monthly stock returns for the sample of firms above and find that tightening shocks lead to a decline in stock returns. In particular, a 1% tightening shock leads to a statistically insignificant drop of 1.4% in monthly stock returns in my sample of firms (Table B.2 in Appendix B.2). Using the S&P 500, Nakamura and Steinsson (2018) find a similar decline of 6.5% and argue that using their structural model without a Fed information effect channel, the decline would have been a massive 11.1%. I am unable to quantify a similar counterfactual in my analysis, as I do not have a structural model of this channel [17]. The decline in stock returns from a tightening

[17] Nakamura and Steinsson (2018) model stocks as an unlevered claim to the consumption stream in the economy

surprise is a puzzle that is difficult to reconile with the *Fed Information Effect* theory and is further complicated by the fact that it requires a model in which good news affects bonds but not stocks.

The negative relationship between tightening shocks and credit spreads is not mechanical because Treasury prices are properly matched with the same duration as recommended by Gilchrist and Zakrajšek (2012). While it could certainly reflect increased optimism of future economic activity, we can also understand the decline in credit spreads through the simple fact that Treasury yields rise by more than corporate bond yields. Why is it reasonable for Treasury yields to rise by more than corporate bond yields when tightening surprises occur? This differential pass-through of monetary policy has been considered by Krishnamurthy and Vissing-Jorgensen (2012) in the context of the supply of safe assets. Under their preferred habitat theory, tightened policy by the Federal Reserve involves the expansion in the supply of Treasury securities in the economy. This abundance of safe assets lowers the safety premium of the risk-free rate and drives the yield up of the Treasury bonds relative to risky bonds. Furthermore, with a lower safety premium, investors choose to invest in riskier corporate bonds which can also drive its yield down and lead to lower credit spreads. They document this negative relationship between the supply of Treasuries and credit spreads across a range of bond-indices and commercial paper (Table 2 of Krishnamurthy and Vissing-Jorgensen (2012)). While the preference for safe assets can be driven by its supply during the period of unconventional monetary policy, it is difficult to argue the same during normal times.

During periods of conventional monetary policy, the Federal Reserve did not engage in asset purchases to drive yields down. Instead, decisions on the target rate were simply announced during FOMC meetings and as long as the market found it credible that it would engage in open market operations to reach that target, interest rates in the market passed through seamlessly. A differential pass through effect can nonetheless still occur if markets are segmented by investor's risk preference. One possibility is to interpret a variant of the prefered habitat theory of Vayanos and Vila (2009) by considering different investors who target specific bond risk. Investors prefer a certain class of securities (maturity or risk). A realistic example could be pension funds who prefer bonds with maturities longer than 15 years in order to hedge long-term liabilities and asset managers who prefer shorter term maturities or mutual funds who are mandated to hold investment grade bonds in their portfolios. A monetary policy surprise in the short term interest rate will lead to underpricing and overpricing of securities in the market. For example, if the federal funds rate unexpectedly rises, this becomes an attractive security to hold relative to the long term interest rate. In this model, a risk-averse arbitrageuer would engage in a "carry-trade" strategy by borrowing at the long term rate in order to buy the short term security and integrate the segmented investors. However, if arbitrageurs are sufficiently risk averse so as to buy and sell only safe assets but not riskier ones, this can lead to a stronger pass-through effect on yields of safe assets. In the same example, safe long term bond yields will increase from the carry-trade strategy while safe short term bond yields decline. As a result, safe and investment grade bonds will respond much more to this monetary policy shock than riskier bonds. In summary, the degree of substitutability between the short term interest rate which is controlled by the Federal Reserve and Treasuries is much greater than the substitutability between the short and long rates of corporate bonds.

A more recent theory which builds on this decoupling in term structure and replaces risk-averse arbitrageuers with investors themselves is the *recruitment channel* posited by Hanson and Stein (2015). Under their framework, news of an increase in the short term interest rate lead investors to rebalance their portfolio from long term assets to short term assets in an effort to maximize their portfolio's yield. This will, in turn, create reduced buying pressure on long term bonds and increase term yields. To fit this narrative with my empirical results, there should again be sufficient risk aversion of investors against rebalancing towards risky short term assets - leading to an attenuated pass-through effect on risky bond yields.

2.6 Conclusion

In this paper, I have documented that tightening surprises induced by FOMC meetings are associated with an overall decline in credit spreads and that this is primarily driven by a reduction in risk premia. Whereas conventional economic theory would suggest that surprise increases in the risk free rate should tighten credit conditions and curtail borrowing, my empirical results show the opposite. This result is supported in event studies using monthly changes in credit spreads, where decomposing its effect into risk premia and expected default is possible, as well as by using daily changes around FOMC announcements. My results lend credence to theories which suggest unexpected tightening is perceived to be good news to the macroeconomy as well as those that suggest a differential pass-through effect to bond yields of different riskiness. A future research direction could be to incorporate this empirical result in a "Fed information" type model of Nakamura and Steinsson (2018). While it is difficult to write down models in which higher interest rate is good news for bonds but not for stocks, one possible channel is if firms borrow through a single bond. Under this framework, a higher interest rate lowers the present value of what must be paid back through the bond and lowers the stock price through the standard discount rate channel. This, however, makes it more difficult to fit with reality, because firms can return to the capital markets again in the future and borrow with other bonds. A central purpose of monetary policy is to effectively manage the economy by influencing investment, consumption, and borrowing decisions. My results shed light on this transmission mechanism by showing that if policy influences the price of borrowing differently for risky and safe assets, perhaps it will also affect the investment decisions differently for risky and safe firms. I explore this issue in the next chapter of my dissertation.

Chapter 3

Investment Channel of Monetary Policy using Credit Spreads

3.1 Introduction

While the heterogenous effects of monetary policy has been widely studied in the context of financial frictions, few papers can agree on a reasonable proxy of this friction. Under the Modigliani and Miller (1958) paradigm, credit spreads are driven entirely by a firm's expected default and risk premia. However, the Great Recession has taught us that movements in spreads can also reflect financial frictions, whereby a deterioration of bank balance sheets led to a lower supply of credit. Our goal in this paper is to study the investment channel of monetary policy by allowing firm sensitivity to depend on credit spreads. The corporate debt market continues to be a large source of funding and accounts for about 37% of net worth for nonfinancial businesses (Figure 3.1). Using information on the spread between the interest a firm must pay to its creditors and a risk-free rate as a proxy for borrowing costs, we take an additional step and decompose this spread into two components: expected losses and risk premia. With heterogeneity of these two components, we ask our main question of how investment responds to monetary policy shocks across firms with higher expected losses and risk premia. While we are unable to disentangle which component of credit spreads matter more for firm investment, our research shows that firms with higher credit spreads face a smaller sensitivity to monetary policy.

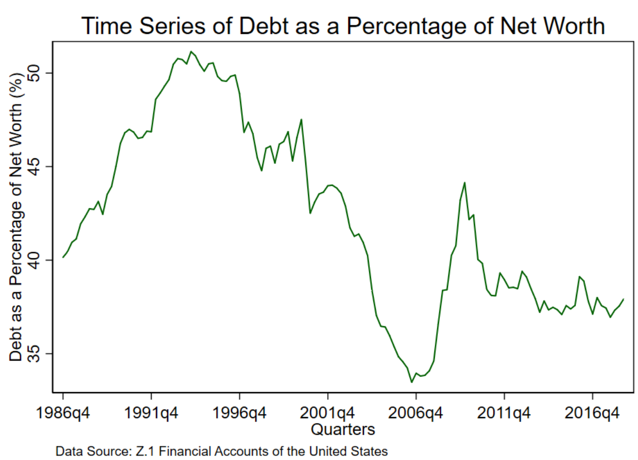


Figure 3.1: Time Series of Corporate Debt as a Percentage of Net Worth for Nonfinancial Corporate Business

This paper seeks to answer the key question raised in the traditional financial accelerator model of Bernanke et al. (1999) of how credit market imperfections affect the aggregate investment response to monetary policy. Under their framework, an expansionary monetary policy shock not only raises investment but also more importantly, the price of capital. This rise in asset prices increases the net worth of firms which drives down their external borrowing costs and further stimulates investment. It is this latter channel of driving down a firm's external borrowing cost that gives rise to the classic amplification effect in the accelerator model. While a number of papers have used size (Oliner and Rudebusch (1996)) and bank credit access (Kashyap et al. (1994)) as an empirical proxy for this external finance, our measure of credit spreads is arguably the most straight forward because it is the actual cost of borrowing that firms pay.

Contrary to the accelerator model which has found that firms with higher costs of financing are more affected by monetary policy, we find that firms with higher expected losses and risk premia face a smaller effect on their investment. In particular, following a 1% expansionary shock, firms with a one standard deviation higher credit spread face a smaller investment impact of 2% four quarters ahead. The departure from the accelerator model comes from the different pass through effects of monetary policy onto corporate bond yields. The argument towards why there should be an amplified investment effect relies on expansionary shocks being passed through directly in the form of lower interest expenses and therefore the firm's need for external financing. This argument, however is challenged under the preferred habitat theory of Krishnamurthy and Vissing-Jorgensen (2012), where investors value safe securities more than they otherwise would during times when Treasury securities or other safe assets are scarce. Expansionary shocks, synonymous with a lower supply of safe assets, drive investors to pursue safer corporate bonds which push down their yields more than riskier bonds. As a result, expansionary monetary policy shocks disproportionately lower the yields of safe bonds relative to riskier bonds which could be a possible reason why riskier firms do not change their investment as much. Riskier firms do not fully benefit from lowered corporate bond yields. We show that over a one day window around Federal Open Market Committee Meetings, a 1% expansionary surprise lowers the yield of safe bonds by 37 basis points and by 10 basis points for high yield risky bonds.

The next section provides a brief survey of related literature. Section 3.3 describes the decomposition methodology. Section 3.4 provides details on the corporate bond data set and monetary policy shocks. Section 3.5 reports the main empirical results and Section 3.6 offers evidence of the pass through effects of monetary policy and Section 3.7 concludes.

3.2 Related Literature

There are a number of papers that have studied the cross sectional effects of monetary policy. Early work by Kashyap et al. (1994) found that bank dependent firms cut their inventories by more than non bank dependent firms in response to monetary tightening. Gertler and Gilchrist (1994), Kashyap and Stein (1995), and Oliner and Rudebusch (1996) all find that small firms contract substantionally more than large firms during periods of tightening. These papers rely on two complementary theories of how financial factors affect the propogation of monetary policy. The first is the "balance sheet theory" which says that capital market imperfections lead to borrowing becoming closely tied to one's balance sheet or net worth. Policies that raise interest rates will weaken the firm's balance sheet and this propogates to affect the firm's spending. The financial accelerator model of Bernanke et al. (1999) develops how adverse effects on one's balance sheet can amplify shocks to the macroeconomy. The second theory that has been empirically tested is the "bank lending channel" of Bernanke and Blinder (1992). In this channel, banks want to hold more reserves, which are insured liabilities, in order to alleviate adverse selection problems. During periods of tight money, there is a lower issuance of these reserves, which tighten liquidity constraints and ultimately contracts lending to the broader economy. Under this framework, small firms, which are more likely to borrow from banks, will become more affected by this loan contraction.

The most relevant paper to ours is Ottonello and Winberry (2018) who interact monetary policy surprises with a firm's leverage to exploit how heterogeneities in this dimension of risk affects its investment sensitivity. They find that firms with low leverage, or safer firms, change their investment much more in response to monetary policy shocks than firms with higher leverage. In other words, higher risk firms which are defined as those with more leverage, have a dampened investment response to monetary policy because they face a steeper marginal cost curve. This result is very much in line with ours except we use the actual price of debt issued by firms as a measure of risk. We feel this is reasonable because this is determined by the market and therefore by efficient markets, reflects all relevant information about the riskiness of a firm. Because Ottonello and Winberry (2018) do not find significant heterogeneities of investment past one quarter, they focus on heterogeneities immediately during the shock impact. We, however, focus on firm investment four quarters ahead which has been shown to be the time frame for which aggregate investment responds (Gertler and Karadi (2015)).

Our paper also connects with another strand of literature on credit spreads and applying Campbell and Shiller (1988a) decompositions to bonds. While Bongaerts et al. (2010) applied a decomposition to the returns on corporate bond indices, this paper uses micro-level data to study the cross section of corporate bond spreads. Elton et al. (2001) account for differences in credit spreads between differently rated bonds based on the average probability of default and loss given default. This paper, however, decomposes credit spreads and allows for time varying expected losses and risk premiums. Gilchrist and Zakrajšek (2012) offer an aggregate decomposition of credit spreads into an expected losses and risk premium component. Their measure of expected losses, however, only uses information based on distance to default and is not an unbiased forecast of realized credit loss. As we will show in the next section, we use all information in our state vector to derive an in sample unbiased estimator of realized credit loss.

It is worth noting that much of the previous literature has relied on using quarterly changes in the federal funds rate as a proxy for monetary policy shocks (Bernanke and Blinder (1992)). This makes identification of an exogenous surprise inherently difficult if we believe that the Federal Reserve also chooses the federal funds rate as a response to developments in the economy. However, we borrow from the literature on identifying monetary policy surprises by measuring interest rate futures changes around a narrow window of FOMC meetings which Kuttner (2001), Gürkaynak et al. (2005), and Gilchrist and Zakrajšek (2012) have shown are reasonable measures of exogenous shocks.

3.3 Decomposition of Corporate Bond Credit Spreads

3.3.1 Log Linearization of Bond Excess Returns

In order to obtain a linear relationship among credit spreads and its two components (bond expected excess returns and credit loss), we follow Nozawa (2017) by log linearizing the bond's excess return. We consider investors who take a long position on individual corporate bond i until it matures or defaults and a short position on a

Treasury bond with the same cash flows as the corporate bond. Upon default of the corporate bond, the investor sells off that position and buys the Treasury bond with the same coupon rate and time to maturity as the defaulted bond.

Let $P_{i,t}$ be the dirty price (includes acrrued interest) of corporate bond i at time t and let $C_{i,t}$ be the coupon rate. The return of this bond next period, $R_{i,t+1}$, is given by:

$$R_{i,t+1} = \frac{P_{i,t+1} + C_{i,t+1}}{P_{i,t}} \tag{3.1}$$

Consider a matching Treasury bond with the same coupon rate and maturity as corporate bond i. If we similarly let $P^f_{i,t}$ and $C^f_{i,t}$ be the price and coupon rate, then the return to this Treasury bond is given by:

$$R^f_{i,t+1} = \frac{P^f_{i,t+1} + C^f_{i,t+1}}{P^f_{i,t}} \tag{3.2}$$

We assume that the rate of credit loss (defined below) for coupons is the same as the rate for the principal because of the lack of information on coupon recovery rates. After log linearizing $R_{i,t+1}$ and $R^f_{i,t+1}$ around the same expansion point $\rho \in [0,1)$, we can express the log return on corporate bond i in excess of the log return on the matching Treasury bond as:

$$r^e_{i,t+1} = \log(R_{i,t+1}) - \log(R^f_{i,t+1}) \approx -\rho s_{i,t+1} + s_{i,t} - l_{i,t+1} + const \tag{3.3}$$

where $s_{i,t}$ is the credit spread and $l_{i,t}$ is the credit loss of bond i at the time t. Details on the derivation of Equation 3.3 are provided in Appendix C.1 and rely heavily on the decomposition of Campbell and Shiller (1988a).

We define the credit spread $s_{i,t}$ and credit loss $l_{i,t}$ as :

$$s_{i,t} = \begin{cases} \log\left(\frac{P^f_{i,t}}{P_{i,t}}\right) & \text{if } t < t_D \\ 0 & \text{otherwise} \end{cases}$$

$$l_{i,t} = \begin{cases} \log\left(\frac{P^f_{i,t}}{P_{i,t}}\right) & \text{if } t = t_D \\ 0 & \text{otherwise} \end{cases}$$

where t_D is the time of default.

The credit spread, $s_{i,t}$ is defined using bond prices rather than yields. This choice was made for two reasons. First, spreads based on bond prices are easier to compute and under the linear structure in Equation 3.3, less prone to approximation errors. Using yields, on the other hand, would require us to compute numerically which makes it hard to express bond returns using a linear function of yield spreads. Second, using price spreads is closely related the commonly used yield spreads, as price changes are approximately equal to yield changes multiplied by duration.

The credit loss, $l_{i,t}$, includes information on both the incidence of default and the loss given default. It is computed using the market prices of corporate bonds upon default and represents the loss investors face when corporate bond i defaults.

Having shown that the excess log return for corporate bond i follows the difference equation in Equation 3.3, we can solve it by iterating forward up to the maturity of the bond T_i.

$$s_{i,t} \approx \sum_{j=1}^{T_i-t} \rho^{j-1} r^e_{i,t+j} + \sum_{j=1}^{T_i-t} \rho^{j-1} l_{i,t+j} + const \tag{3.4}$$

Since Equation 3.4 holds for each period t, the expression also holds under expectation. Taking the time t conditional expectations on both sides of Equation 3.4, we get:

$$s_{i,t} \approx E\left[\sum_{j=1}^{T_i-t} \rho^{j-1} r^e_{i,t+j} \ \ |\mathcal{F}_t\right] + E\left[\sum_{j=1}^{T_i-t} \rho^{j-1} l_{i,t+j} \ \ |\mathcal{F}_t\right] + const \tag{3.5}$$

where $\mathcal{F}_t$ is the information set of agents at time t. Equation 3.5 shows that variations in credit spreads can be decomposed into long run expected excess returns (r^e_i) or credit loss (l^t_i). Since corporate bonds have fixed cash flows, the only source of cash flow risk is credit loss.

3.3.2 Estimation of Decomposition

Having decomposed credit spreads into a linear relationship between expected excess returns and expected losses, we can estimate the conditional expectations in Equation 3.5 using a Vector Auto Regression (VAR). We define a vector of state variables:

$$X_{i,t} = \begin{pmatrix} r^e_{i,t} & d_{i,t}s_{i,t} & \tau_{i,t}PD_{i,t} & r^{EQ}_{i,t} & bm_{i,t} \end{pmatrix}' \tag{3.6}$$

which follows the dynamics:

$$X_{i,t+1} = AX_{i,t} + W_{i,t+1} \tag{3.7}$$

and where $d_{i,t}$ is a vector of dummy variables for credit ratings defined as $d_{i,t} = (1 \;\; d_{i,t}^{A} \;\; d_{i,t}^{Baa} \;\; d_{i,t}^{Ba})$ such that $d_{i,t}^{\theta}$ is a dummy for rating θ, $\tau_{i,t}$ is the duration of bond i, $PD_{i,t}$ is its probability of default, and $r_{i,t}^{EQ}$ is the issuer's excess equity return, and $bm_{i,t}$ is its book to market ratio. We take the product between the bond's duration (τ) and the probability of default (PD) given by Merton (1974)'s model because price spreads and risk premia decrease further out in the horizon. We adjust for this fact by including this term. The interaction term between the bond's spread and credit rating allows the coefficients to be a function of the bond's credit rating.

We define selection vectors $e_1 = (1 \;\; 0 \;\; 0 \;\; ... \;\; 0\;)$ and $e_2 = (0 \;\; 1 \;\; 0 \;\; ... \;\; 0\;)$ which "pick out" the elements $r_{i,t}^{e}$ and $s_{i,t}$ respectively. We can easily see that $E\left[r_{i,t+j}^{e}|X_{i,t}\right]$ $= e_1 A^j X_{i,t}$

Consider the re-arranged Equation 3.3 and taking the conditional expectation, this can be expressed as

$$\begin{aligned}
E\left[l_{i,t+j}|X_{i,t}\right] &= E\left[-\rho s_{i,t+1} + s_{i,t} - r_{i,t+1}^{e}|X_{i,t}\right] \\
&= E\left[-\rho e_2 X_{i,t+j} + e_2 X_{i,t+j-1} - e_1 X_{i,t+j}|X_{i,t}\right] \\
&= \underbrace{\left[-\rho e_2 + e_2 A^{-1} - e_1\right]}_{e_L} A^j X_{i,t}
\end{aligned}$$

Having developed these two expressions, we can return to Equation 3.5

$$
\begin{aligned}
s_{i,t} &\approx E\left[\sum_{j=1}^{T_i-t} \rho^{j-1} r^e_{i,t+j} \;\; |X_{i,t}\right] + \left[\sum_{j=1}^{T_i-t} \rho^{j-1} l_{i,t+j} \;\; |X_{i,t}\right] \\
&\approx \sum_{j=1}^{T_i-t} \rho^{j-1} e_1 A^j X_{i,t} + \sum_{j=1}^{T_i-t} \rho^{j-1} e_L A^j X_{i,t} \\
&\approx e_1 A (I-A)^{-1} \left(I - (\rho A)^{T_i-t}\right) + e_L A (I-A)^{-1} \left(I - (\rho A)^{T_i-t}\right) X_{i,t} \\
&\approx \underbrace{e_1 G(T_i) X_{i,t}}_{\text{Excess Returns}} + \underbrace{e_L G(T_i) X_{i,t}}_{\text{Expected Losses}}
\end{aligned}
\tag{3.8}
$$

where $G(T_i) = A(I-A)^{-1}\left(I - (\rho A)^{T_i-t}\right)$. With this, we now apply Equation 3.8 to each individual bond i and decompose spreads into excess returns (risk premium) and expected losses.

3.4 Data

3.4.1 Corporate Bonds

We construct the panel data of U.S. corporate bond prices from January 1973 to December 2016 combining the *Lehman Brothers Fixed Income Database*, the *Mergent FISD/NAIC Database*, *TRACE*, *DataStream and Merrill Lynch*. Overall, prices are reasonably close to each other and we do not see any trends in gaps in historical data across databases.

When there are overlaps among the five databases, we prioritize in the following order: the *Lehman Brothers Fixed Income Database*, *TRACE*, *Mergent FISD/NAIC*, *DataStream and Merrill Lynch*. If the observation for a defaulted bond is missing in the databases above, we use Moody's *Default Risk Service* to complement the price upon default. For the exercise of calls and call prices, we use *Mergent FISD*, and for bonds that are in *Lehman Brothers Fixed Income Database* but not in *Mergent FISD*, we use the changes in amount outstanding to identify the exercise of calls and assume that the call price is the market price. We remove junior bonds, bonds with floating rates, and with option features other than callable bonds.

We apply three filters to remove observations that are likely to be subject to erroneous recording. First, we remove the price observations that are higher than matching Treasury bond prices which would suggest a negative credit spread. Second, we drop price observations below one cent per dollar. Third, we remove return observations that show a large bounceback. Specifically, we compute the product of the adjacent return observations and remove both observations if the product is less than -0.04. After applying the filters, the resulting sample is an unbalanced panel data of 937,418 bond month observations for 20,820 bonds over 528 months. In order to compute excess returns and credit spreads, we construct the prices of the synthetic Treasury bonds that match the corporate bonds using the Federal Reserve's constant-maturity yields data. The methodology is detailed in Appendix C.2.1. *CRSP* and *Compustat* provide the stock prices and accounting information. In Appendix C.2.3, we describe the matching procedure between bond data and firm balance sheet variables. We obtain economic activity data from *FRED*.

3.4.2 Monetary Policy Shocks

Monetary policy shocks are measured as intradaily changes in various futures contracts around a window of Federal Open Market Committee (FOMC) announcement dates. The literature has shown that by focusing on the unanticipated changes of interest rate futures around a narrow announcement interval, we can better isolate changes in market expectations of policy (Kuttner (2001), Gürkaynak et al. (2005), and Gertler and Karadi (2015)). Because these changes are measured in a sufficiently narrow window, they are uncontaminated by other sources of information besides monetary policy. More importantly, this approach disentangles the impact of policy response towards changes in economic developments which is an endogeneity issue that can plague studies using lower frequency data. We compute shocks over a tight window which is measured 10 minutes prior to the announcement and 20 minutes after the announcement. Details on the construction of these shocks are provided in Appendix C.2.2. We consider FOMC meetings from February 1984 to May 2, 2018 which is a total of 333 meetings. Among all the futures contracts, we choose to focus on the first federal funds rate and the fourth eurodollar. From the monthly time series in Figure 3.2, it is clear that during the ZLB period (right of black dashed line), there was no surprise movements in the federal funds rate (green line) and more variation in the fourth eurodollars futures contract (orange line). The fourth eurodollar futures contract corresponds to a bet on what the short term London Inter-bank Offered Rate (LIBOR) will be fourth quarters, or one year ahead. Thus, it paints a better picture of the market perception on the future path of policy one year out.

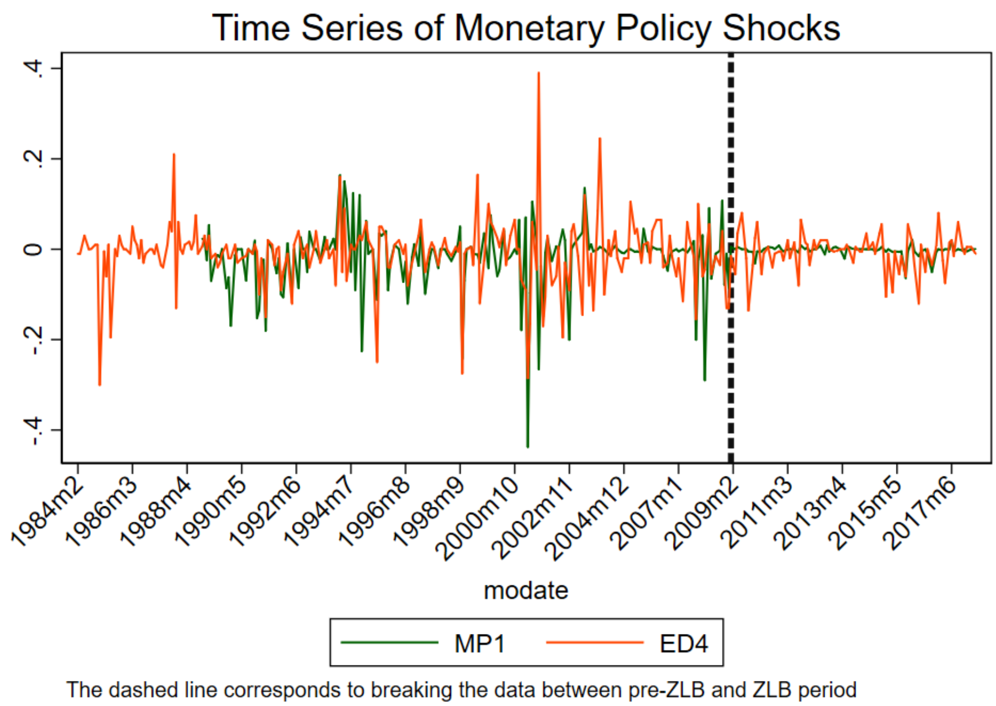


Figure 3.2: Monetary Policy Shocks

This time series shows the monthly average monetary policy shocks of $MP1$, the scaled surprise in current month federal funds rate futures contract, and $ED4$, the surprise in the fourth eurodollar futures contract. The green line corresponds to $MP1$ and the orange line corresponds to $ED4$. The pre-ZLB period is to the left of the black dashed line and the ZLB period is to the right of it. Appendix C.2.2 provides details on its construction.

3.4.3 Summary Statistics

Having completed the matching process between a bond and the balance sheet information of its issuer, we now explore the heterogeneities that exist in the data. In particular, we're interested in differences between the two components of bond spreads, investment, and other balance sheet variables. Table 3.1 reports the summary statistics of two components of credit spreads, bond maturity, investment, and various characteristics of the firm that will be used as controls. Figure 3.3 plots the histograms of all the variables computed and shows large heterogeneities that exist across firms.

	N	Mean	SD	25-Percentile	50-Percentile	70-Percentile	95-Percentile
Expected Credit Loss	9247	0.025	0.025	0.005	0.020	0.038	0.071
Excess Return	9247	0.084	0.060	0.047	0.071	0.106	0.196
Maturity	9247	12.615	6.179	7.046	11.963	17.915	22.636
Investment	8878	0.013	0.021	0.001	0.012	0.025	0.049
Book to Market Ratio	7552	1.026	0.521	0.570	0.995	1.429	1.918
Leverage	8390	0.362	0.108	0.278	0.368	0.446	0.525
Sales Growth	8651	0.022	0.142	-0.049	0.025	0.104	0.257
Size (log Assets)	9244	7.977	1.298	7.074	7.874	8.789	10.393
Current Assets as a Share of Total Assets	8138	0.292	0.194	0.114	0.247	0.444	0.635

Table 3.1: Summary Statistics of Bond Characteristics

The table reflects quarterly data from Compustat from 1973Q4 - 2016Q4. All variables are winsorized at the 2nd and 98th percentile. Definitions of each variable are described in Appendix C.2.3.

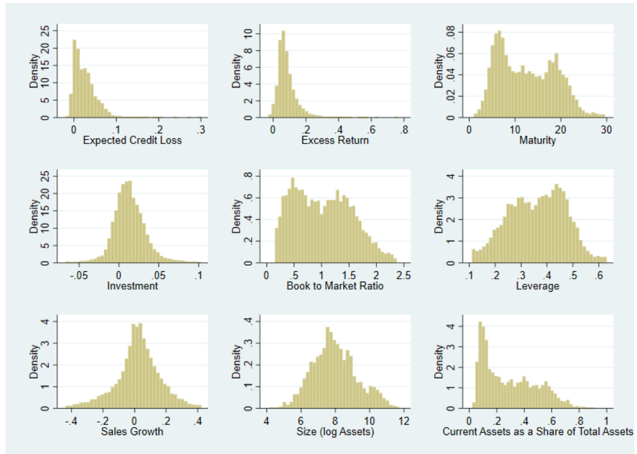


Figure 3.3: Histogram of Bond Characteristics

3.4.4 Aggregate Relationship

3.4.4.1 Investment

How well does the aggregate investment that we compute align with what FRED reports? We compute the market weighted average of investment across all firms in our sample from 1976-2016 and compare this with annual changes in Real Private Nonresidential Fixed Investment attained from FRED. This measure corresponds to changes in spending on plant and equipment and is closely related to our firm level measure from Compustat of quarterly changes in capital (plant, property, and equipment).

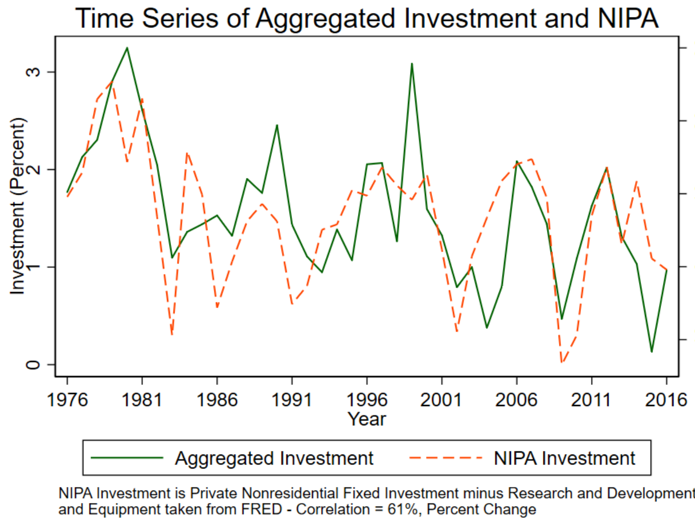


Figure 3.4: Time Series of Aggregate Investment

This figure is an annual time series from 1976-2016 of our Aggregated Investment and National Income and Product Accounts of the United States (NIPA) Investment (FRED Code: `PNFI_PCH`) minus Research and Development (FRED Code: `Y006RC1Q027SBEA`) minus Equipment (FRED Code: `Y033RC1Q027SBEA`). The Aggregated Investment is computed as the market weighted average of firm level investment where firm level investment scaled by total assets is winsorized at the 5th and 95th level. NIPA Investment is defined as the seasonally adjusted annual percentage change in real private nonresidential fixed investment.

Figure 3.4 plots the two series, where the solid line corresponds to a value weighted average of firm investment and the dashed line is obtained from FRED and adjusted to better match our definition. The correlation between the two series is 61%. There are several reasons to account for the difference between our measure and the raw investment data from FRED. One, the measure reported by FRED comes from the Bureau of Economic Analysis and consists of expenditures on structures, equipment, and intellectual property and other subcategories within them. The measure we use from Compustat, however, only includes expenditures on plant, property, and equipment. We attempt to mitigate this problem by removing intellectual property (research and development) as well as equipments to better match our definition from Compustat. Second, our investment is computed from a subsample of firms who issue corporate bonds and thus, those who do not rely solely on bank financing.

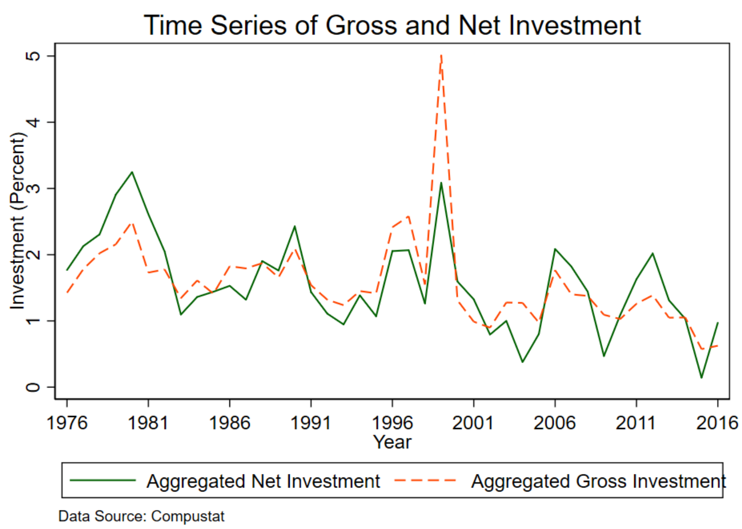


Figure 3.5: Time Series of Aggregate Gross and Net Investment

This figure is an annual time series from 1976-2016 of our Aggregated Net Investment (`ppentq`) and Aggregated Gross Investment (`ppegtq`). The Aggregated Investment is computed as the market weighted average of firm level investment where firm level investment scaled by total assets is winsorized at the 5th and 95th level. NIPA Investment is defined as the seasonally adjusted annual percentage change in real private nonresidential fixed investment.

The aggregation by NIPA, however, consists of all firms indiscriminatly. Despite these differences, the aggregate investment that we compute matches reasonably well with the reported measure with a sharp decline during the Great Recession of 2008. It is worth mentioning that what is deemed *investment* on FRED is actually *capital expenditure* in our sample. Therefore we treat the level of investment reported in FRED as k and compute annual changes on this measure and plot this as the dashed line in Figure 3.4. As described in Appendix C.2.4, we use net investment rather than gross investment. While gross investment (`ppegtq`) is more closely tied to the investment decisions a firm makes, we are constrained by the significantly fewer observations that exist. Net investment (`ppentq`), which considers changes in net plant, property, and equipment has much more observations and is also used by Ottonello and Winberry (2018). We include a comparison between gross and net investment in Figure 3.5 and it is clear that there is a large outlier and spike in the early 2000s. This gives us another reason to focus on net investment.

3.4.4.2 Credit Spreads

Having shown that our aggregated investment variable matches well with what is reported in NIPA, we now turn our attention to our measure of credit spreads. Our measure of credit spread and its components (expected default and risk premium) is closely related to that of Gilchrist and Zakrajšek (2012). In their paper, they first regress firm level credit spreads on a firm specific measure of default as well as a vector of bond specific characteristics to isolate a predicted level of credit spread attributed to expected default risk (analogous to expected losses in our framework). They then compute an unweighted cross sectional average of these fitted values to denote the average predicted spreads each month ($\hat{S}_t^{GZ}$). They then construct an aggregate monthly credit spread index, (GZ Spread hereafter) by taking an unweighted cross sectional average of credit spreads across all firms and their liabilities and define the excess bond premium (analogous to expected excess return) as the component of GZ Spread net of expected defaults. In essence, Gilchrist and Zakrajšek (2012) provide an aggregate measure of credit spread and decompose it into a component related to expected default risk and a residual component to capture risk compensation over and above default. Therefore, it is natural to aggregate our measure of expected losses ($s^d_{i,t}$) and expected excess returns ($s^r_{i,t}$) which came from the decomposition in Section 3.3 and compare it with fitted values of the GZ-Spread and the Excess Bond Premium, respectively. The GZ Spread and excess bond premium is also a widely used benchmark in the literature (Gertler and Karadi (2015)).

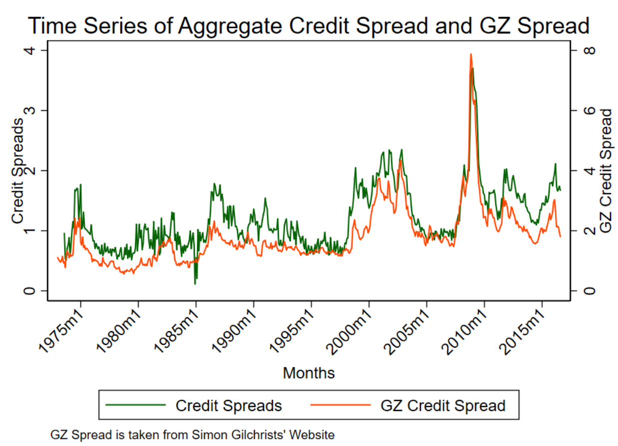


Figure 3.6: Time Series of Aggregate Credit Spreads s and GZ-Credit Spread

This figure is a monthly time series of our excess return component which is computed as an unweighted cross sectional average across all firms each month. It is compared with the GZ Credit Spread from Gilchrist and Zakrajšek (2012) which is attained from Simon Gilchrists' website.

Figure 3.6 plots the time series of our aggregate credit spread and the GZ-Spread collected from Gilchrist and Zakrajšek (2012). The two series are highly correlated at 90% which shows that our sample is representative of what was used in their study. The GZ credit spread is simply an arithmetic average of the credit spreads on outstanding bonds each month. An important distinction between our sample is that Gilchrist and Zakrajšek (2012) include callable bonds (about two-thirds of their sample) which means that the issuer has the right to pay back interest and principal ahead of schedule. We remove callable bonds because it interacts with monetary policy is a meaningful way. When interest rates are lowered, this raises the likelihood of issuers calling their bonds and refinancing their debt at lower rates. By removing callable bonds, we remove this additional channel[1].

Figure 3.7 and Figure 3.8 show the time series between our two components (s^r and s^d) with the GZ-Excess Bond Premium and Expected Default, respectively. The correlation in Figure 3.7 between the expected excess returns component and GZ-Excess Bond Premium is 66%. The expected excess returns component matches many of the peaks and troughs present in GZ EBP. The correlation in Figure 3.8 is 81%. A key difference worth noting is that the expected default computed from GZ (orange line in Figure 3.8) is limited to information from distance to default, whereas our measure uses all information in the state vector from Equation 3.6. In addition, our measure of expected losses is an in-sample unbiased estimator of realized credit loss whereas GZ's measure is not an unbiased forecast.

[1]We do not remove make-whole callable bonds which include provisions that sufficiently compensate the holder of the bond in the event the call option is executed. This compensation removes any economic benefit from early execution.

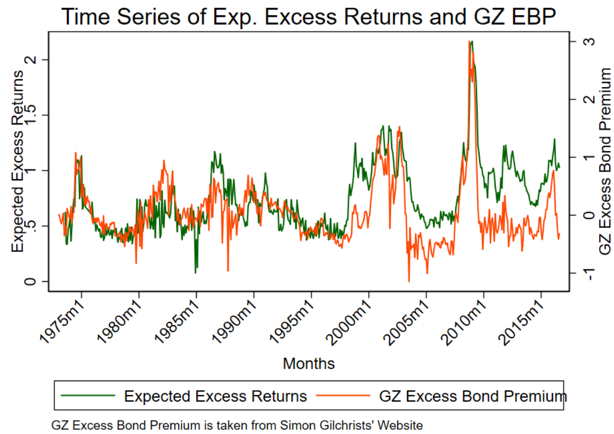


Figure 3.7: Time Series of Expected Excess Returns s^r and GZ-Excess Bond Premium

This figure is a monthly time series of our expected excess return component which is computed as an unweighted cross sectional average across all firms each month. It is compared with the GZ Excess Bond Premium from Gilchrist and Zakrajšek (2012) which is attained from Simon Gilchrists' website.

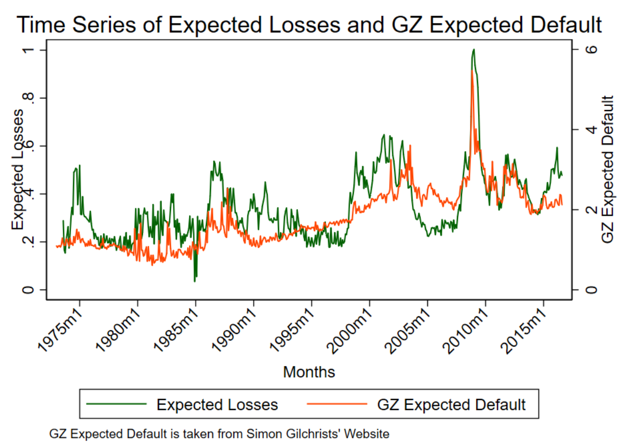


Figure 3.8: Time Series of Expected Losses s^d and GZ-Expected Default

This figure is a monthly time series of our expected loss component which is computed as an unweighted cross sectional average across all firms each month. It is compared with the GZ Expected Default from Gilchrist and Zakrajšek (2012) which is attained from Simon Gilchrists' website. This measure is not directly reported in the data base but is easily computed as the difference between the spread and excess bond premium, both of which are reported.

3.5 Empirical Analysis

3.5.1 Monetary Policy Transmission Mechanism

In this section, we revisit the widely studied question of how monetary policy affects firm investment. However, given the large endogeneity concerns of policy responding to aggregate investment, we focus on the surprise and unexpected component of monetary policy[2]. Studying the transmission mechansim is an important first step to ensure that the shocks and investment variable that we use are sensible and generate results in line with what the literature has found. An early paper by Bernanke and Gertler (1995) estimated a VAR and found that residential and business fixed investment declined around six months following a monetary tightening. Using a model with nominal rigidities, Christiano et al. (2005) and Gertler and Karadi (2011) also conclude that monetary policy tightening surprises reduce investment. Given the large differences in the macroeconomy between the period prior to the zero lower bound (1986Q1-2008Q4) and the period during it (2009Q1-2016Q4), we separate these periods in our analysis. Although we are interested in understanding the investment response at the individual firm level, it is worth first examining whether the relationship holds in the aggregate. We do this by taking a value weighted average of investment across all firms each quarter and estimate the following time series

[2] We also consider the relationship between aggregate investment and quarterly changes in the short term interest rates (3 month, 1 Year, and 2 Year Constant Maturity Treasury Yields) and find statistically insignificant results. This perhaps arises because of the endogeneity issue discussed and motivates focusing on the surprise component of monetary policy.

regression:

$$\Delta\log K_{t+1} = \beta_0 + \beta_1 MPS_t + \beta_2 Z_t + \epsilon_{t+1} \tag{3.9}$$

where $K_{t+1} = \sum_{i=1}^{N} w_{i,t}\Delta\log k_{i,t+1}$, the market weighted average of investment in quarter $t+1$, is measured as the change in capital from quarter t to quarter $t+1$ and MPS_t is the normalized monetary policy shock such that positive values denote **easing surprises**. If the transmission mechanism is to work as the literature suggests, we expect a positive coefficient - that is, expansionary surprises lower borrowing costs and investment increases. Like much of the literature, we use $MP1$, the surprise component in the current month federal funds rate futures contract, as a proxy for monetary policy shocks during the Pre-ZLB period. In addition, we also include the residuals from the projection of $ED4$, the surprise component in the fourth eurodollar futures contract, onto $MP1$ and denote this as the "path" surprise. Z_t is a vector of aggregate firm controls including the book to market ratio, leverage, sales growth, size, and current assets as a share of total assets.

We first estimate Equation 3.9 without controlling for these additional variables and present the results for three sample periods in Table 3.2a. Column (1) shows that a 1% expansionary surprise leads to a statistically significant 3% increase in aggregate investment. This effect can also be seen during the pre-ZLB period (Column 2). In Column (3), the effect reverses where expansionary surprises lead to a decline in investment. One potential reason why this reversal occurs is the "information effect" of unconventional monetary policy documented by Nakamura and Steinsson (2018).

Under their framework, expansionary surprises lead to decreased optimism about economic fundamentals and a drop in expected output growth. While we include the zero lower bound period in our subsequent analysis, we draw stronger statistical significance by focusing on the Pre-ZLB period. Table 3.2b shows that by controlling for additional firm characteristics and macroeconomic variables, the results remain largely the same. We next examine whether the transmission of policy on aggregate investment holds in subsequent quarters. Table 3.3 reports the results of regressing changes in aggregate investment two, three, and four quarters ahead on the monetary policy surprises. While the results are insignificant for the two (Panel 3.3a) and three (Panel 3.3b) quarter ahead investment, the positive coefficient on the path shock confirms the intuition that easing surprises lead to higher investment. More importantly, four quarter ahead aggregate investment shows the strongest significance in response to monetary policy shocks - a result in line with that of Gertler and Karadi (2015).

(a) Aggregate Investment without controls

	(1) Full Sample 1986Q1-2016Q4	(2) Pre-ZLB 1986Q1-2008Q4	(3) ZLB 2009Q1-2016Q4
MP1	0.0358**	0.0297*	
	(0.0172)	(0.0164)	
PATH	-0.00858	0.00229	
	(0.0148)	(0.0165)	
ED4			-0.0623**
			(0.0279)
Constant	0.00966***	0.0110***	0.00721***
	(0.000684)	(0.000803)	(0.00106)
Observations	113	81	32
R^2	0.0396	0.0342	0.0907
Controls	No	No	No

(b) Aggregate Investment with controls

	(1) Full Sample 1986Q1-2016Q4	(2) Pre-ZLB 1986Q1-2008Q4	(3) ZLB 2009Q1-2016Q4
MP1	0.0396***	0.0429***	
	(0.0143)	(0.0150)	
PATH	-0.00355	-0.00220	
	(0.0135)	(0.0162)	
ED4			-0.0344
			(0.0379)
Constant	0.0598*	0.0536	-0.000526
	(0.0321)	(0.0364)	(0.172)
Observations	113	81	32
R^2	0.395	0.434	0.238
Controls	Yes	Yes	Yes

Table 3.2: One Quarter Ahead Aggregate Investment

This table presents the results of estimating Equation 3.9 for both without controlling (Panel 3.2a) and with controlling (Panel 3.2b) for other aggregate variables Z. These controls include firm level such as book to market ratio, leverage, sales growth, size, and current assets as a share of total assets. Aggregate controls include GDP growth, unemployment rate, and inflation. Investment is winsorized at the 5th and 95th percentile prior to the aggregation. Column (1) reports estimates using the full sample (1986Q1-2016Q4), Column (2) reports from the Pre-ZLB period (1986Q1-2008Q4), and Column (3) the period during the zero-lower bound (2009Q1-2016Q4). Standard errors are White standard errors.

(a) Two Quarter Ahead Aggregate Investment

	(1) Full Sample 1986Q1-2016Q4	(2) Pre-ZLB 1986Q1-2008Q4	(3) ZLB 2009Q1-2016Q4
MP1	-0.00953	-0.00953	
	(0.0179)	(0.0179)	
PATH	0.0106	0.0106	
	(0.0163)	(0.0163)	
ED4			0.0257
			(0.0232)
Constant	0.0473	0.0473	-0.423**
	(0.0471)	(0.0471)	(0.157)
Observations	112	112	31
R^2	0.116	0.116	0.345
Controls	Yes	Yes	Yes

(b) Three Quarter Ahead Aggregate Investment

	(1) Full Sample 1986Q1-2016Q4	(2) Pre-ZLB 1986Q1-2008Q4	(3) ZLB 2009Q1-2016Q4
MP1	0.0211	0.0211	
	(0.0185)	(0.0185)	
PATH	0.0247*	0.0247*	
	(0.0140)	(0.0140)	
ED4			-0.0122
			(0.0410)
Constant	0.0837**	0.0837**	0.0692
	(0.0357)	(0.0357)	(0.198)
Observations	111	111	30
R^2	0.159	0.159	0.0699
Controls	Yes	Yes	Yes

(c) Four Quarter Ahead Aggregate Investment

	(1) Full Sample 1986Q1-2016Q4	(2) Pre-ZLB 1986Q1-2008Q4	(3) ZLB 2009Q1-2016Q4
MP1	0.0232	0.0247*	
	(0.0143)	(0.0144)	
PATH	0.0345**	0.0323**	
	(0.0139)	(0.0154)	
ED4			0.0356
			(0.0527)
Constant	-0.00795	-0.00846	0.130
	(0.0253)	(0.0302)	(0.138)
Observations	109	81	28
R^2	0.398	0.394	0.298
Controls	Yes	Yes	Yes

Table 3.3: Aggregate Investment Monetary Policy Transmission

This table presents the results of estimating Equation 3.9 for different quarters ahead while controlling for other aggregate variables Z. The sample is winsorized at the 5th and 95th percentile on the variable of investment relative to market assets prior to the aggregation. Column (1) reports estimates using the full sample (1986Q1-2016Q4), Column (2) reports from the Pre-ZLB period (1986Q1-2008Q4), and Column (3) the period during the zero-lower bound (2009Q1-2016Q4). Standard errors are White standard errors.

The results in Table 3.2 and Table 3.3 reveal that the transmission mechanism largely behaves in the way others have found in the literature during normal times. Given the ambiguities relying on aggregate data, we next turn our attention to the cross section and ask whether the effect is stronger at the individual firm level. We do this by focusing on the disaggregated panel and estimate the following pooled regression, which is an analog of Equation 3.9:

$$\Delta \log\, k_{i,t+1} = \beta_0 + \beta_1 MPS_t + \beta_2 Z_{i,t} + \epsilon_{i,t+1} \tag{3.10}$$

where $\Delta\log\, k_{i,t+1}$ is investment in quarter $t+1$ measured as the change in capital from quarter t to quarter $t+1$ and MPS_t is the normalized monetary policy shock such that positive values denote easing surprises. As in the aggregate, we also include various firm controls ($Z_{i,t}$) such as its book to market ratio, leverage, sales growth, size, and current assets as a share of total assets and estimate results in the period before and during the ZLB. Because there exists correlation within quarters, we cluster our standard errors by quarter. Clustering standard errors at the quarterly level allows for correlation within a quarter but rules out correlation across quarters.

	(1) Full Sample 1984Q1-2016Q4	(2) Pre-ZLB 1984Q1-2008Q4	(3) ZLB 2009Q1-2016Q4
MP1	0.0317**	0.0316**	
	(0.0146)	(0.0146)	
PATH	-0.0103	0.00816	
	(0.0179)	(0.0193)	
ED4			-0.0912***
			(0.0278)
Constant	0.0368***	0.0358***	0.0267***
	(0.00242)	(0.00261)	(0.00475)
Observations	25672	17701	7971
R^2	0.0234	0.0260	0.0259
Controls	Yes	Yes	Yes

Table 3.4: Firm Level Monetary Policy Transmission of Investment

Results from estimating Equation 3.10 using sample of non-financial firms that are matched to bonds. Column (1) reports estimates using the full sample (1984Q1-2016Q4), Column (2) reports from the Pre-ZLB period (1984Q1-2008Q4), and Column (3) the period during the zero-lower bound (2009Q1-2016Q4). MP1 is the surprise component in the current month federal funds rate futures contract scaled by the number of days relative to the FOMC meeting. ED4 is the surprise component of the fourth eurodollar futures contract. Both shocks are normalized so that positive values correspond to expansionary shocks (decrease in interest rates). For more details on the construction of MP1 and ED4, see Gürkaynak et al. (2005). Firm controls include book to market ratio, leverage, sales growth, size, and current assets as a share of total assets. Standard errors are clustered by quarters.

Table 3.4 shows the results of estimating Equation 3.10 over various sample periods. We find that, much like the aggregate response, an expansionary surprise leads to an increase in investment for the full sample and prior to the zero lower bound. The results are quite similar to the one quarter ahead results on the aggregate level in Table 3.2. Given that the aggregate results in Table 3.3 shows the strongest statistical significance for four quarter ahead investment, we continue focusing on this time horizon in the subsequent sections.

3.5.2 Heterogeneities of the Transmission Mechanism

In this section we allow the investment sensitivity to monetary policy shocks to vary with firm level credit spreads ($s_{i,t}$). In particular, we interact the shocks with credit spreads and estimate the following regression:

$$\Delta \log\, k_{i,t+4} = \beta_0 + \beta_1 MPS_t + \beta_2 s_{i,t} MPS_t + \gamma_1 Z_{i,t-1} + \gamma_2 Y_{t-1} + \epsilon_{i,t+4} \tag{3.11}$$

where $\Delta \log\, k_{i,t+4}$ is four quarter ahead investment defined as $k_{i,t+4}$-$k_{i,t+3}$, $s_{i,t}$ is firm i's normalized credit spread at quarter t, MPS_t is the intradaily monetary policy shock aggregated at the quarterly level, $Z_{i,t}$ is a vector of firm level controls (book-to-market ratio, leverage, sales growth, size, and current assets as a share of total assets) in quarter t, and Y_{t-1} is a vector of aggregate controls (GDP growth, unemployment rate, and inflation) one quarter before the shocks. We control variables one quarter prior to the realization of the shock to avoid them reacting to the monetary policy shock. The coefficient of interest is β_2 which describes how investment sensitivity changes for firms with one standard deviation higher credit spread. The results for estimating Equation 3.11 is reported in Table 3.5 and suggests that a one standard deviation higher level of credit spreads reduces the investment sensitivity to monetary policy surprises by 2.14% in the full sample (Column 1) and 2% in the pre-ZLB period (Column 2). During the ZLB period (Column 3), however, there is an insignificant effect. Having conditioned the sensitivity on the overall level of credit spreads, we now ask whether this effect can be decomposed into expected default ($s^d_{i,t}$) and expected excess returns ($s^r_{i,t}$). We use the two components of credit spreads to examine the role they play in the investment channel of monetary policy. We exploit the rich heterogeneity that we observe in the expected loss and risk premium component across bonds of different firms to ask the following question: are firms that with higher expected default and risk premium, more or less responsive to monetary policy?

	(1) Full Sample 1984Q1-2016Q4	(2) Pre-ZLB 1984Q1-2008Q4	(3) ZLB 2009Q1-2016Q4
MP1	0.0129	0.0118	
	(0.0209)	(0.0218)	
$s \times MP1$	$\boxed{-0.0214^{***}}$	$\boxed{-0.0199^{**}}$	
	(0.00742)	(0.00816)	
ED4			0.0463
			(0.0439)
$s \times ED4$			$\boxed{-0.0255}$
			(0.0261)
Constant	0.0352***	0.0472***	0.00979
	(0.00414)	(0.00617)	(0.00868)
Observations	21224	15059	6165
R^2	0.0249	0.0303	0.0273
Controls	Yes	Yes	Yes

Table 3.5: Heterogeneity of Transmission Mechanism using $\Delta k_{i,t+4}$

Results from estimating Equation 3.11 using sample of non-financial firms that are matched to bonds. Column (1) reports estimates using the full sample (1984Q1-2016Q4), Column (2) reports from the Pre-ZLB period (1984Q1-2008Q4), and Column (3) the period during the zero-lower bound (2009Q1-2016Q4). MP1 is the surprise component in the current month federal funds rate futures contract scaled by the number of days relative to the FOMC meeting. ED4 is the surprise component of the fourth eurodollar futures contract. Both shocks are normalized so that positive values correspond to expansionary shocks (decrease in interest rates). s^d and s^r are standardized to have mean 0 and standard deviation of 1. For more details on the construction of MP1 and ED4, see Gürkaynak et al. (2005) and Appendix C.2.2. Firm controls include book to market ratio, leverage, sales growth, size, and current assets as a share of total assets. Aggregate controls include GDP growth rate, unemployment rate, and inflation. Standard errors are clustered by quarters.

The empirical specification is :

$$\Delta \log\, k_{i,t+4} = \beta_0 + \beta_1 MPS_t + \beta_2 \underbrace{E_t\left[\sum_j \rho^{j-1} l_{i,t+j}\right]}_{s^d_{i,t}} MPS_t + \beta_3 \underbrace{E_t\left[\sum_j \rho^{j-1} r^e_{i,t+j}\right]}_{s^r_{i,t}} MPS_t + \\ + \gamma_1 Z_{i,t-1} + \gamma_2 Y_{t-1} + \epsilon_{i,t+4} \tag{3.12}$$

where $\Delta \log\, k_{i,t+4}$ is four quarter ahead investment, $\sum_j \rho^{j-1} l_{t+j}$ is the expected long run expected credit loss of firm i's bond denoted as s^d, $\sum_j \rho^{j-1} r^e_{t+j}$ is the expected excess return (risk premium) of firm i's bond denoted as s^r, MPS_t is the intradaily monetary policy shock aggregated at the quarterly level, $Z_{i,t}$ is a vector of firm level controls (book-to-market ratio, leverage, sales growth, size, and current assets as a share of total assets) in quarter t, and Y_{t-1} is a vector of aggregate controls (GDP growth, unemployment rate, and inflation) one quarter before the shocks. In addition to reporting the results of Equation 3.12 which focuses on the four quarter change in capital, we also consider different horizons such as $\log\, k_{i,t+j} - \log\, k_{i,t+j-1}$, $j = 0$ ... 3 and provide the results in Appendix C.3. These results are reported in Table C.1, Table C.2, Table C.3, and Table C.4 where the sum of coefficients vary in magnitude and statistical significance.

Table 3.6 reports the results of Equation 3.12 and considers the effects of monetary policy on the four quarter change in investment. It shows that by including both interactions with expected default (s^d) and expected excess returns (s^r), the coefficients are insignificant individually. The results suggest that we cannot disentangle which component of credit spreads matter more in explaining the smaller effect of monetary policy. This arises because of the high correlation among the two series. However, the sum of coefficients for the full-sample and pre-ZLB are negative and statistically different from zero. In particular, Column (1) finds that for the full sample (1984Q1-2016Q4), in response to a 1% expansionary shock, firms with a one standard deviation higher exposure to both components face a smaller sensitivity of four quarter ahead investment by 2%. In the pre-ZLB period (Column 2), firms are 1.88% less responsive to monetary policy shocks. To put these magnitudes into context, Ottonello and Winberry (2018) find that firms with a one standard deviation higher leverage reduce their sensitivity by 74 bp one quarter ahead, or 2.96% four quarters ahead. However, they do not find statistical significance past one quarter and continue their entire analysis for a quarter ahead. Column (3) of Table 3.6 reports results for the zero-lower bound period and finds a reduced sensitivity of 2.8% although it is not statistically significant.

The results in Table 3.6 report standard errors that are clustered at the (quarterly) date level. This means that observations may be correlated within each quarter but uncorrelated across quarters. This seems reasonable given that monetary policy surprises in quarter t will affect firms similarly in that quarter but differently one or two quarters ahead. However, this also raises potential concerns of serial correlation if firm i has residuals that are correlated across time. We test for serial correlation by regressing residuals for each firm i on its one quarter lag. We estimate the following regression for each firm i.

$$\hat{\epsilon}_{i,t} = \rho\hat{\epsilon}_{i,t-1} + \eta_{i,t} \tag{3.13}$$

We find that the average absolute value of ρ across all firms is 0.263 suggesting that serial correlation is not a big problem. Furthermore, the left hand side variables do not overlap (e.g. $k_{i,t+4} - k_{i,t+3}$ does not overlap with $k_{i,t+3} - k_{i,t+2}$) which alleviates some concerns of serial correlation. If however, we tried to forecast investment as $k_{i,t+4} - k_{i,t}$, using MPS_t, this will give rise to serious concerns of serial correlation. More specifically, the residuals $\epsilon_{i,t+4} - \epsilon_{i,t}$ and $\epsilon_{i,t+5} - \epsilon_{i,t+1}$ would each contain the shock $\epsilon_{i,t+4} - \epsilon_{i,t+1}$ which is a concern addressed by Hodrick (1992).

	(1) Full Sample 1984Q1-2016Q4	(2) Pre-ZLB 1984Q1-2008Q4	(3) ZLB 2009Q1-2016Q4
MP1	0.0127	0.0107	
	(0.0215)	(0.0223)	
$s^d \times MP1$	0.00840	-0.0000532	
	(0.0212)	(0.0200)	
$s^r \times MP1$	-0.0286	-0.0187	
	(0.0202)	(0.0182)	
ED4			0.0516
			(0.0450)
$s^d \times ED4$			-0.00920
			(0.0370)
$s^r \times ED4$			-0.0188
			(0.0503)
Constant	0.0349***	0.0481***	0.00858
	(0.00424)	(0.00613)	(0.00916)
Coefficient Sum	$\boxed{-0.0202}$	$\boxed{-0.0188}$	$\boxed{-0.0280}$
SE Sum	0.00767	0.00834	0.0227
t-stat	-2.636	-2.252	-1.232
Observations	20890	14862	6028
R^2	0.0247	0.0299	0.0281
Controls	Yes	Yes	Yes

Table 3.6: Heterogeneity of Transmission Mechanism with Credit Spread Components

Results from estimating Equation 3.12 using sample of non-financial firms that are matched to bonds. Column (1) reports estimates using the full sample (1984Q1-2016Q4), Column (2) reports from the Pre-ZLB period (1984Q1-2008Q4), and Column (3) the period during the zero-lower bound (2009Q1-2016Q4). MP1 is the surprise component in the current month federal funds rate futures contract scaled by the number of days relative to the FOMC meeting. ED4 is the surprise component of the fourth eurodollar futures contract. Both shocks are normalized so that positive values correspond to expansionary shocks (decrease in interest rates). s^d and s^r are standardized to have mean 0 and standard deviation of 1. For more details on the construction of MP1 and ED4, see Gürkaynak et al. (2005) and Appendix C.2.2. Firm controls include book to market ratio, leverage, sales growth, size, and current assets as a share of total assets. Aggregate controls include GDP growth rate, unemployment rate, and inflation. Standard errors are clustered by quarters.

As an additional robustness check to see whether four quarter ahead investment is meaningfully impacted, we consider a different left hand side variable that holds an initial capital level prior to the monetary policy surprise log $k_{i,t-1}$ fixed and measures changes in capital j quarters ahead. We compute the following difference, log $k_{i,t+j}$ −

log $k_{i,t-1}$ for $j = 1 \ldots 5$ and substitute that as our left hand side variable in Equation 3.12.

$$\log k_{i,t+j} - \log k_{i,t-1} = \beta_0 + \beta_{j,d} s^d_{i,t} \times MPS_t + \beta_{j,r} s^r_{i,t} \times MPS_t + \gamma_1 Z_{i,t-1} + \gamma_2 Y_{t-1} + \epsilon^j_{i,t} \tag{3.14}$$

This is essentially Jordà (2005)'s local projections methodology of estimating impulse response functions, which as he discusses, has several advantages. Using this method, we avoid extrapolation and compounding errors in the parameter estimates β_j as we increase the horizon. Rather than reporting the regression results in a table, we plot the coefficient sums on the interaction term, $\beta_{j,d} + \beta_{j,r}$ as well as a 95% confidence interval in Figure 3.9. From Figure 3.9, we can see that the impact increases as we go further out into longer horizons with the 1-Quarter ahead leading to a 2.3% reduced sensitivity on investment and the 4-Quarters ahead leading to a 4.8% reduction. Furthermore, at the 5-Quarter ahead horizon, the impact is no longer statisically significant. We repeat the exercise for the pre-ZLB sample (Figure 3.10) and find similar results.

In particular, for the pre-ZLB sample, 1-Quarter ahead investment falls by 1.8% from higher exposure to the credit spread components and 4.3% 4-Quarters ahead. Similarly, looking past four quarters does not yield statistically significant results which again implies that monetary policy has strong effects just one year out. The results in Figure 3.9 and Figure 3.10 have much larger magnitudes than the regression results reported earlier. This is because of the way we define investment as being changes in capital relative to one quarter before period t. Thus, it's likely that capital accumulates much more yielding larger estimates of investment. In results not reported, we re-estimate these regressions using gross investment and find that the results are insignificant. This again, could be due to the much fewer observations and large outliers that exist in the data.

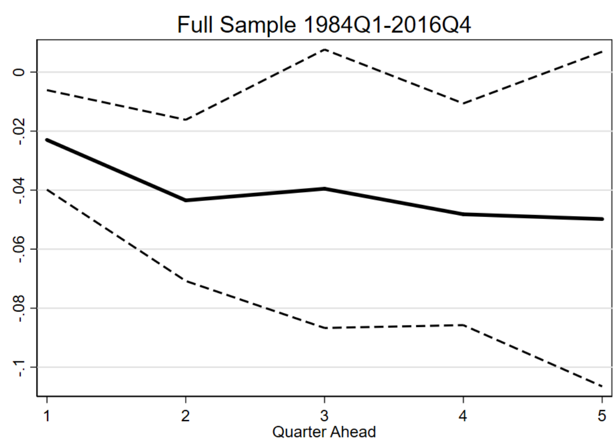


Figure 3.9: Impulse Response Function Full Sample

This figure plots the sum of coefficient on $s^d \times MP1$ and $s^r \times MP1$ for the full sample (1984Q1 - 2016Q4) as a function of the time horizon j. For example, the 2-Quarter ahead coefficient corresponds to a left hand side variable of $\log k_{i,t+2} - \log k_{i,t-1}$ while the 4-Quarter ahead coefficient corresponds to $\log k_{i,t+4} - \log k_{i,t-1}$. The black line is the point estimate while the dashed lines are a 95% confidence interval.

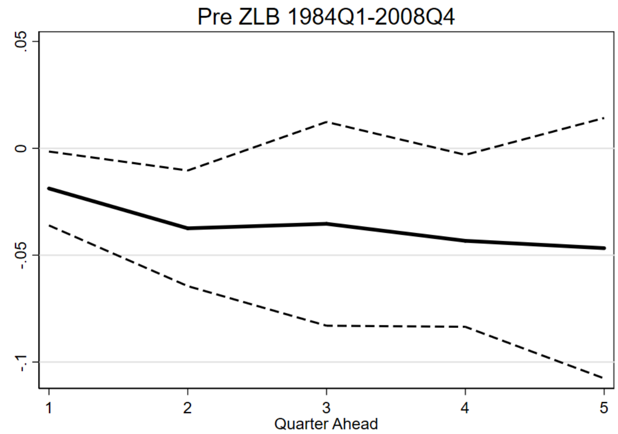
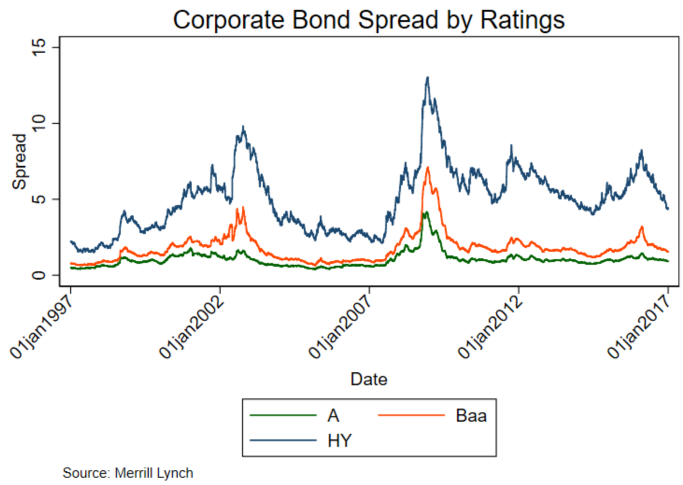


Figure 3.10: Impulse Response Function Pre-ZLB Sample

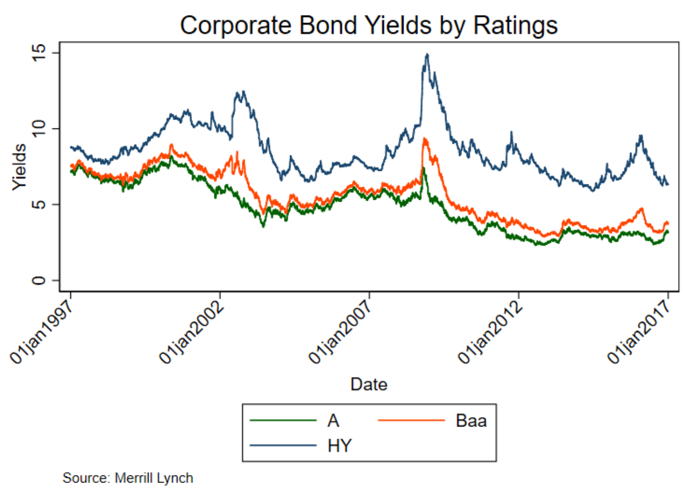
This figure plots the sum of coefficient on $s^d \times MP1$ and $s^r \times MP1$ for the pre ZLB sample (1984Q1 - 2008Q4) as a function of the time horizon j. For example, the 2-Quarter ahead coefficient corresponds to a left hand side variable of $\log k_{i,t+2} - \log k_{i,t-1}$ while the 4-Quarter ahead coefficient corresponds to $\log k_{i,t+4} - \log k_{i,t-1}$. The black line is the point estimate while the dashed lines are a 95% confidence interval.

3.6 Pass-Through Effects of Monetary Policy

The previous section showed that monetary policy has a dampened effect on investment for firms with a higher expected losses and risk premium component. In this section, we explore whether the differential impact occurs because firms with higher credit spreads face an unequal pass through effect on their corporate bond yields during monetary easing compared with those that are deemed safer. Figure 3.11 shows the daily time series of corporate bond spread and yields by different ratings.



(a) Corporate Bond Spread



(b) Corporate Bond Yield

Figure 3.11: Corporate Bond Spreads and Yields by Ratings

This figure is a daily time series of average corporate bond spreads (Panel A) and average corporate bond yields (Panel B) from January 1997-December 2016 (5,042 observations). The blue line corresponds to High Yield (HY) risky bonds, the orange line corresponds to Baa bonds, and the green line corresponds to an average of Aa+ and Aa bonds. We remove callable bonds and financial firms (SIC:6000-7000). We take a weighted average of observations by the face value of the bond and winsorize spreads and yields at the 2nd and 98th percentile level to remove outliers. The data comes from Merrill Lynch.

The High Yield (HY) blue line corresponds to bonds with lower credit ratings than Baa while the orange (Baa) and green (A) lines are investment grade bonds [3]. Unsuprisingly, the overall level of spreads and yields are noticeably higher for riskier bonds. One theory as to why there could be an unequal pass through of monetary policy is the preferred habitat theory of Vayanos and Vila (2009) where the term structure results from an interaction between investor clienteles and risk averse arbitrageurs. The corporate-bond class system very much exists in the real world where many types of mutual funds have mandates to hold investment grade bonds [4]. Under this theory, the propogation of changes in expectation of short term rates towards corporate bond yields is weakened for bonds which investors are more risk averse towards. As a result, the monetary policy transmission mechanism is dampened and risky corporate bonds underreact.

Another complementary theory of the unequal pass-through effect of monetary policy is the safety premium theory of Krishnamurthy and Vissing-Jorgensen (2012). Under this theory, investors value safety qualities inherent in Treasuries during times when the supply of Treasuries are especially low. As a result, the yield on Treasuries is low relative to riskier bonds when the quantity of Treasuries is low. This logic also extends to corporate bonds that differ in their safety. Krishnamurthy and Vissing-Jorgensen (2012) empirically find that when the supply of Treasuries are low, yields on AA bonds fall more than yields on BAA resulting in the spread (y^{BAA}-y^{AA}) to

[3] The high yield market in the United States is now worth about $ 1.2 trillion.
[4] "Buttonwood: Scavenging in the junk yard" The Economist December 1st, 2018

rise. This points to evidence of a priced long-term safety attribute which is driven solely by the supply of Treasuries. A detailed discussion of these theories is provided in my second chapter.

We address these implications by estimating an event study regression of the one day change in corporate bond yields on changes in the fourth eurodollar futures contract (ED4 monetary policy surprise). The underlying assumption of this regression is that $ED4$, the fourth eurodollars futures contract, is a reasonable proxy for the path of future policy. We estimate this regression for investment grade safe bonds (Aa+ and A), intermediate bonds (Baa), and high yield risky bonds (HY). Under the preferred habitat and safety premium theory, we would expect to see a smaller sensitivity on corporate bond yields for riskier bonds. Table 3.7 present the regression results for one day and two day changes in corporate bond yields. If we focus on Table 3.7a, we see that a 100 basis point decline in the fourth eurodollar futures corresponds to a 37 basis point fall in the safest corporate bond yields, 36 basis points in intermediate bonds, and 10 basis point for the riskiest bonds. A similar pattern emerges for the two day change in Table 3.7b where moving from the safest to riskiest bonds lead to a lower pass through onto yields. It is interesting to note that the pass through for the two day change is also larger than that of the one day change which can attributed to potential stale prices over the one day change.

(a) Pass Through Effect on One-Day Corporate Bond Yields

	(1) Δy^{AA}_{1-Day} Safe Bonds	(2) Δy^{BAA}_{1-Day} Intermediate Bonds	(3) Δy^{HY}_{1-Day} Risky Bonds
ED4	-0.368***	-0.359***	-0.107*
	(0.0540)	(0.0497)	(0.0567)
Constant	0.00112	0.00696	0.00638
	(0.00504)	(0.00437)	(0.00689)
Observations	92	92	92
R^2	0.321	0.382	0.0242

(b) Pass Through Effect on Two-Day Corporate Bond Yields

	(1) Δy^{AA}_{2-Day} Safe Bonds	(2) Δy^{BAA}_{2-Day} Intermediate Bonds	(3) Δy^{HY}_{2-Day} Risky Bonds
ED4	-0.446***	-0.445***	-0.265**
	(0.0994)	(0.0983)	(0.112)
Constant	-0.00277	0.00336	0.00308
	(0.00884)	(0.00848)	(0.0104)
Observations	90	90	90
R^2	0.197	0.214	0.0643

Table 3.7: Pass Through Effect on Corporate Bond Yields

Results from estimating a regression of the one day (Panel 3.7a) and two day (Panel 3.7b) change in corporate bond yields during FOMC meetings on changes in the fourth eurodollar futures contract (ED4) for the pre-ZLB period (February 5, 1997 - December 11, 2007). We exclude the September 17, 2001 meetings due to the terrorist attacks. We remove callable bonds and financial firms (`SIC`:6000-7000). We take a weighted average of observations by the face value of the bond and winsorize spreads and yields at the 2nd and 98th percentile level to remove outliers. The data comes from Merrill Lynch. Column (1) reports estimates using a sample of the safest bonds (Aa), Column (2) reports estimates using a sample of intermediate rated bonds (Baa), and Column (3) reports estimates using a sample of the riskiest bonds (HY). ED4 is the surprise component of the fourth eurodollar futures contract which is normalized so that positive values correspond to expansionary shocks (decrease in interest rates). Robust white standard errors are reported in parenthesis.

The results in Table 3.7a and Table 3.7b use data from Merrill Lynch which could raise concerns of stale prices, where the reported price does not accurately reflect information that occurs on the actual FOMC day. One possibility of why this occurs is because the bond prices we see on an FOMC day was actually agreed upon a day or two prior to the FOMC announcement. If that is the case, we won't see accurate movements in yields in our sample which focuses on announcement dates. We consider the two day change in Table 3.7b which still yields statistically significant results. To further mitigate these concerns, we turn to TRACE data which reports dates on when the exact transaction terms are agreed upon. This is as opposed to the delivery date when the bond is actually passed on to the counter party and where stale prices are a concern. We re-estimate these daily regressions using execution dates that fall on FOMC meetings and report the results in Table 3.8. Using transactions prices that are executed on FOMC announcement dates, we see that there is a limited pass through effect of 60bp to safe bonds and 23 basis points to riskier bonds.

	(1) Δy^{AA}_{2-Day} Safe Bonds	(2) Δy^{BAA}_{2-Day} Intermediate Bonds	(3) Δy^{HY}_{2-Day} Risky Bonds
ED4	-0.602***	-0.577***	-0.229
	(0.184)	(0.168)	(0.481)
Constant	-0.0110	0.0147	0.00185
	(0.0163)	(0.0216)	(0.0482)
Observations	44	44	44
R^2	0.231	0.135	0.00499

Table 3.8: Pass Through Effect on Two-Day Corporate Bond Yields using TRACE

Results from estimating a regression of the two day change in corporate bond yields during FOMC meetings on changes in the fourth eurodollar futures contract (ED4) for the pre-ZLB period (February 5, 1997 - December 11, 2007). We exclude the September 17, 2001 meetings due to the terrorist attacks. We remove callable bonds and financial firms (`SIC`:6000-7000). We take a weighted average of observations by the face value of the bond and winsorize spreads and yields at the 2nd and 98th percentile level to remove outliers. The data comes from TRACE and use trade execution dates. Column (1) reports estimates using a sample of the safest bonds (Aa), Column (2) reports estimates using a sample of intermediate rated bonds (Baa), and Column (3) reports estimates using a sample of the riskiest bonds (HY). ED4 is the surprise component of the fourth eurodollar futures contract which is normalized so that positive values correspond to expansionary shocks (decrease in interest rates). Robust white standard errors are reported in parenthesis.

	(1) Δy^{HY-AA}_{1-Day} Risky Minus Safe Yields	(2) Δs^{HY-AA}_{1-Day} Risky Minus Safe Spreads
ED4	0.261***	0.310***
	(0.0775)	(0.0799)
Constant	0.00526	0.00573
	(0.00886)	(0.0104)
Observations	92	92
R^2	0.0784	0.0823

Table 3.9: Pass Through Effect on Risky minus Safe Bonds

Column (1) reports results from estimating a regression of the one day change in risky bond yields minus safe bond yields during FOMC meetings on changes in the fourth eurodollar futures contract (ED4) for the pre-ZLB period (February 5, 1997 - December 11, 2007). Column (2) repeats the same regression except using risky spreads minus safe spreads. We exclude the September 17, 2001 meetings due to the terrorist attacks. We remove callable bonds and financial firms (`SIC`:6000-7000). We take a weighted average of observations by the face value of the bond and winsorize spreads and yields at the 2nd and 98th percentile level to remove outliers. The data comes from Merrill Lynch. ED4 is the surprise component of the fourth eurodollar futures contract which is normalized so that positive values correspond to expansionary shocks (decrease in interest rates). Robust white standard errors are reported in parenthesis.

The empirical results above suggest a differential pass-through monetary policy effect between risky and safe firms. A more direct test is to take the difference of yields (and spreads) between risky and safe assets and directly regress the 1-day change on the monetary policy shock. In Table 3.9, we test the hypothesis that there are differences in pass-throughs on yields and spreads between risky and safe bonds. In particular, I take the difference between risky and safe yields (spreads) and compute the one day change of this difference. The null hypothesis is that the coefficient on $ED4$ is zero - that is, there are no significant differences between risky and safe yields (spreads) chnages in response to monetary policy shocks. The regression results in Table 3.9 suggest that we can reject this null hypothesis. Furthermore, the positive coefficient on $ED4$ for both yields and spreads show that in response to expansionary surprises, safe yields (spreads) fall by much more than risky yields (spreads), thus suggesting a differential pass through effect between risky and safe bonds.

3.7 Conclusion

By applying a Campbell-Shiller decomposition, we are able to disentangle the direct cost of external finance into a component related to expected losses and another to risk premium. We show empirically that firms with higher expected losses and risk premium component of credit spreads face a dampened investment response to expansionary surprises, although we are unable to disentangle which piece matters more. Our paper contributes to the voluminous literature on the monetary policy transmission mechanism by conditioning on these two components and documenting the opposite of an amplification effect that the previous literature has found. We relate this dampened investment response to a growing literature on the pass through effects of monetary policy whereby Federal Reserve announcements differentially impact risky and safe securities. In particular, the safety premium and preferred habitat theory postulates that expansionary shocks pass through more easily for safer bonds because of a safety premium that investors value. A future research direction could be to directly model the empirical results of our paper. One possible mechanism is such that firms with higher expected losses are closer to default and face an intensified conflict between bond and equity holders, leading to a decline in investment.

Our paper is also of topical interest in the context of the unintended consequences of monetary policy. The dual mandate of monetary policy has always been price stability and employment but in recent years, more attention has been paid on the effects on inequality and welfare[5]. While inequality in the context of individuals and consumers is not applicable in our context, we can consider a channel by which firms are affected differentially. More specifically, is it the case that monetary policy is promoting industry concentration of larger firms at the expense of smaller firms? Our results do not provide a definitive answer to this complicated question but the results

[5]Innocent bystanders? Monetary policy and inequality in the US (2014 VOX) and Monetary Policy and inequality: A new channel (2018 VOX)

of my second chapter suggests that monetary policy does not pass through equally to the bond yields of risky and safe firms. This chapter suggests that this differential pass-through can carry over and have an impact on firm investment and allow firms with lower credit spreads to invest more. Larger firms, which have better access to funding, will benefit disproportionately to expansionary policy and can perhaps lead to greater concentration of large firms. This is related to the normative issue of "creative destruction" of undesirable firms, whereby better firms replace outdated ones. Our results again, are only indicative that policy disproportionately benefits safe firms relative to riskier ones.

Appendix A

Appendix to Chapter 1

A.1 Solving the Bank's Problem

$$
\begin{aligned}
\pi = \max_{S, i^L, i^D} \quad & (1+i^L)L + (1+i)S - (1+i^D)D \\
\text{subject to} \quad & L + S = D + E_0(i) \\
& \psi^L L \leq \pi \\
& \psi^D D \leq S \\
& 0 \leq i^D \\
& L = L(i^L) \\
& D = D(i^D)
\end{aligned}
\tag{A.1}
$$

In order to solve the bank's problem, first write the Lagrangian:

$$\mathcal{L} = (1+i^L)L + (1+i)S - (1+i^D)D - \mu(L+S-D-E_0(i)) + \lambda^D(S - \psi^D D)$$
$$+\lambda^L((1+i^L)L + (1+i)S - (1+i^D)D - \psi^L L) \tag{A.2}$$

Taking the first-order condition with respect to S:

$$\mu = (1+i)(1+\lambda^L) + \lambda^D \tag{A.3}$$

Taking the first-order condition with respond to i^L:

$$\begin{aligned} L + (1+i^L)L^{'} - \mu L^{'} + \lambda^L(L + (1+i^L)L^{'}) - \lambda^L\psi^L L^{'} &= 0 \\ (1+i^L)(L^{'}(1+\lambda^L)) &= \mu L^{'} - (1+\lambda^L)L + \lambda^L\psi^L L^{'} \\ (1+i^L) &= \frac{1}{(1+\lambda^L)}\left[\mu - (1+\lambda^L)\frac{L}{L^{'}} + \lambda^L\psi^L\right] \end{aligned} \tag{A.4}$$

We can substitute Equation A.3 and define $\frac{L^{'}}{L}$ = -ϵ^L as the semi-elasticity to get:

$$\begin{aligned} (1+i^L) &= \frac{1}{(1+\lambda^L)}\left[(1+i)(1+\lambda^L) + \lambda^D - (1+\lambda^L)\frac{L}{L^{'}} + \lambda^L\psi^L\right] \\ (1+i^L) &= (1+i) - \frac{\lambda^D}{1+\lambda^L} - \underbrace{\frac{L}{L^{'}}}_{\frac{1}{\epsilon^L}} + \frac{\lambda^L}{1+\lambda^L}\psi^L \\ i^{*L} &= i + \underbrace{\frac{1}{\epsilon^L}}_{\text{mark-up}} + \underbrace{\frac{\lambda^L}{1+\lambda^L}\psi^L + \frac{\lambda^D}{1+\lambda^L}}_{\text{capital constraint}} \end{aligned} \tag{A.5}$$

Taking the first-order condition with respond to i^D:

$$\begin{aligned}
-D-(1+i^D)D^{'}+\mu D^{'}-\lambda^D\psi^D D^{'}-\lambda^L(D+(1+i^D)D^{'}) &= 0\\
D+(1+i^D)D^{'}+\lambda^L(D+(1+i^D)D^{'}) &= \mu D^{'}-\lambda^D\psi^D D^{'}\\
(1+i^D)(D^{'}(1+\lambda^L)) &= \mu D^{'}-(1+\lambda^L)D-\lambda^D\psi^D D^{'}\\
(1+i^D) &= \frac{1}{1+\lambda^L}\left[\mu-(1+\lambda^L)\frac{D}{D'}-\lambda^D\psi^D\right]
\end{aligned} \tag{A.6}$$

We can substitute Equation A.3 and define $\frac{D^{'}}{D}=\epsilon^D$ as the semi-elasticity to get:

$$\begin{aligned}
(1+i^D) &= \frac{1}{1+\lambda^L}\left[(1+i)(1+\lambda^L)+\lambda^D-(1+\lambda^L)\frac{D}{D'}-\lambda^D\psi^D\right]\\
(1+i^D) &= (1+i)+\frac{\lambda^D}{1+\lambda^L}-\underbrace{\frac{D}{D'}}_{\epsilon^D}-\frac{\lambda^D}{1+\lambda^L}\psi^D\\
i^{*D} &= i-\underbrace{\frac{1}{\epsilon^D}}_{\text{mark-down}}+\underbrace{\frac{\lambda^D}{1+\lambda^L}(1-\psi^D)}_{\text{liquidity constraint}}
\end{aligned} \tag{A.7}$$

A.2 Solving the Household's Problem

The household chooses the amount of deposits to hold at bank i, D_i by taking as given the mark-up or spread of the bank s_i subject to the constraint that aggregate deposits are formed as a composite good produced by a set of N banks.

$$\begin{aligned} \min_{D_i} \quad & \sum_{i=1}^{N} D_i s_i \\ \text{subject to} \quad & D = \left(\frac{1}{N}\sum_{i=1}^{N} D_i^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}} \end{aligned} \tag{A.8}$$

Let λ be the Lagrange multiplier on the aggregate deposit constraint. Then, taking the first order condition with respect to D_i:

$$\begin{aligned} s_i - \lambda\frac{\eta}{\eta-1}\left(\frac{1}{N}\sum_{i=1}^{N} D_i^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}-1}\left(\frac{\eta-1}{\eta}\frac{1}{N}D_i^{-\frac{1}{\eta}}\right) = 0 \\ s_i = \frac{\lambda}{N}D^{\frac{1}{\eta}}D_i^{-\frac{1}{\eta}} \Rightarrow D_i^{-\frac{1}{\eta}} = \frac{N s_i D^{-\frac{1}{\eta}}}{\lambda} \Rightarrow D_i = D\left(\frac{\lambda}{N s_i}\right)^{\eta} \end{aligned} \tag{A.9}$$

Define the weighted average deposit spread as

$$s \equiv \frac{1}{N}\sum_{i=1}^{N}\frac{D_i}{D}s_i \tag{A.10}$$

We can substitute in the expression from Equation A.9 of s_i into the definition of s to get the following:

$$\begin{aligned} s &= \frac{1}{ND}\sum_{i=1}^{N} D_i^{1-\frac{1}{\eta}} D^{\frac{1}{\eta}}\frac{\lambda}{N} \\ &= \frac{\lambda}{ND}D^{\frac{1}{\eta}}\left(\frac{1}{N}\sum_{i=1}^{N} D_i^{\frac{\eta-1}{\eta}}\right) \\ &= \frac{\lambda}{N}D^{\frac{1-\eta}{\eta}}D^{\frac{\eta-1}{\eta}} \\ &= \frac{\lambda}{N} \end{aligned} \tag{A.11}$$

Using this expression, we can easily see that

$$s_i = s(\frac{D_i}{D})^{-\frac{1}{\eta}} \Rightarrow D_i = (\frac{s_i}{s})^{-\eta} D \tag{A.12}$$

which is the household demand function for deposits. This expression can be substituted into the aggregate deposit condition to get the following:

$$\begin{aligned}
D &= \left[\frac{1}{N} \sum_{i=1}^{N} D^{\frac{\eta-1}{\eta}} (\frac{s}{s_i})^{\eta-1} \right]^{\frac{\eta}{\eta-1}} \\
1 &= \left[\frac{1}{N} \sum_{i=1}^{N} (\frac{s}{s_i})^{\eta-1} \right]^{\frac{\eta}{\eta-1}} \\
s^{-\eta} &= \left[\frac{1}{N} \sum_{i=1}^{N} {s_i}^{1-\eta} \right]^{\frac{\eta}{\eta-1}} \\
s &= \left[\frac{1}{N} \sum_{i=1}^{N} {s_i}^{1-\eta} \right]^{\frac{1}{1-\eta}}
\end{aligned} \tag{A.13}$$

As an auxiliary equation for further use, we can take the derivative of Equation A.13 with respect to s_i to get:

$$\begin{aligned}
\frac{\partial s}{\partial s_i} &= \frac{1}{1-\eta} \left[\frac{1}{N} \sum_{i=1}^{N} {s_i}^{1-\eta} \right]^{\frac{\eta}{1-\eta}} \frac{1-\eta}{N} s_i^{-\eta} \\
&= \left[s^{1-\eta} \right]^{\frac{\eta}{1-\eta}} \frac{1}{N} s_i^{-\eta} \\
&= \frac{1}{N} \underbrace{\left(\frac{s_i}{s} \right)^{-\eta}}_{\frac{D_i}{D}}
\end{aligned} \tag{A.14}$$

We're now ready to derive an expression of market power for banks. We can differentiate Equation A.12 with respect to the spread of each bank s_i:

$$
\begin{aligned}
D_i &= D(\frac{s_i}{s})^{-\eta} \\
\frac{\partial D_i}{\partial s_i} &= \frac{\partial D}{\partial s}\frac{\partial s}{\partial s_i}(\frac{s_i}{s})^{-\eta} - D\eta(\frac{s_i}{s})^{-\eta-1}\left(\frac{1}{s}\right) + D\eta\left(\frac{s_i}{s}\right)^{-\eta-1}\left(\frac{s_i}{s^2}\right)\frac{\partial s}{\partial s_i} \\
&= \frac{\partial D}{\partial S}\frac{1}{N}\frac{D_i}{D}(\frac{s_i}{s})^{-\eta} - D\eta(\frac{s_i}{s})^{-\eta}\left(\frac{1}{s_i}\right) + D\eta\left(\frac{s_i}{s}\right)^{-\eta}\left(\frac{1}{s}\right)\left(\frac{1}{N}\frac{D_i}{D}\right) \\
&= \frac{1}{N}\left(\frac{\partial D}{\partial s}\frac{s}{D}\right)\frac{D_i}{s}\left(\frac{s_i}{s}\right)^{-\eta} - \eta\frac{D_i}{s_i} + \frac{\eta}{N}\frac{D_i}{s}\frac{D_i}{D} \qquad \text{(A.15)} \\
\frac{\partial D_i}{\partial s_i}\frac{s_i}{D_i} &= \frac{1}{N}\left(\frac{\partial D}{\partial s}\frac{s}{D}\right)\left(\frac{s_i}{s}\right)^{1-\eta} - \eta\left[1 - \frac{1}{N}\frac{s_i}{s}\frac{D_i}{D}\right]
\end{aligned}
$$

$$
\frac{\partial D_i/D_i}{\partial s_i/s_i} = \frac{1}{N}\left(\frac{\partial D/D}{\partial s/s}\right) - \eta\left(1 - \frac{1}{N}\right)
$$

A.3 Deriving the Optimal Deposit Spread

This section derives Equation 1.18, the aggregate deposit elasticity and uses this to find a closed form solution for the bank's optimal deposit spread (Equation 1.19). We begin by expressing three first order conditions that must be true for the household. First, households must be indifferent between banks at the margin:

$$
\frac{D_i}{D} = \left(\frac{s_i}{s}\right)^{-\eta} \tag{A.16}
$$

Second, households must be indifferent between cash and deposits at the margin:

$$\frac{D}{M} = \delta^{\epsilon} \left(\frac{s}{i}\right)^{-\epsilon} \tag{A.17}$$

Third, households must be indifferent between liquidity and bonds at the margin:

$$\frac{l}{W} = \lambda^{\rho} s_l^{-\rho} \tag{A.18}$$

where $s_l \equiv \frac{M}{l} i + \frac{D}{l} s$ - the weighted average foregone interest cost that households incur to obtain liquidity. The proof requires a number of auxiliary equations which will be useful.

First, differentiating Equation A.18 with respect to the deposit spread s, we get

$$\begin{aligned} l &= W \lambda^{\rho} s_l^{-\rho} \\ \frac{\partial l}{\partial s} &= \frac{\partial W}{\partial s} \lambda^{\rho} s_l^{-\rho} - \rho W \lambda^{\rho} s_l^{-\rho-1} \frac{\partial s_l}{\partial s} \\ &= \frac{\partial W}{\partial s} \lambda^{\rho} s_l^{-\rho} - \rho \frac{W}{s_l} \frac{l}{W} \frac{\partial s_l}{\partial s} \\ \frac{\partial l}{\partial s} &= -\rho \frac{l}{s_l} \frac{\partial s_l}{\partial s} \end{aligned} \tag{A.19}$$

where the last equality comes from taking the limit $\lambda \to 0$.

Second, using Equation A.17, we can express M as:

$$M = D \delta^{-\epsilon} \left(\frac{s}{i}\right)^{\epsilon} \tag{A.20}$$

which after substituting into Equation 1.12 and differentiating, we have:

$$
\begin{aligned}
l &= \left(\left(D\delta^{-\epsilon} \left(\frac{s}{i} \right)^{\epsilon} \right)^{\frac{\epsilon-1}{\epsilon}} + \delta D^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}} \\
&= D \underbrace{\left[\delta^{1-\epsilon} \left(\frac{i}{s} \right)^{1-\epsilon} + \delta \right]^{\frac{\epsilon}{\epsilon-1}}}_{\kappa}
\end{aligned}
\tag{A.21}
$$

$$
\begin{aligned}
l &= D\kappa \\
\frac{\partial l}{\partial s} &= \kappa \frac{\partial D}{\partial s} + D \frac{\partial \kappa}{\partial s}
\end{aligned}
$$

Combining Equation A.19 and A.21, we get

$$
\begin{aligned}
\kappa \frac{\partial D}{\partial s} + D \frac{\partial \kappa}{\partial s} &= -\rho \frac{l}{s_l} \frac{\partial s_l}{\partial s} \\
\kappa \frac{\partial D}{\partial s} + D \frac{\partial \kappa}{\partial s} &= -\rho \frac{l}{s_l} \left[\delta^{\epsilon} \left(\frac{s_l}{s} \right)^{\epsilon} \right]
\end{aligned}
\tag{A.22}
$$

$$
\begin{aligned}
\left[\delta^{1-\epsilon} \left(\frac{i}{s} \right)^{1-\epsilon} + \delta \right]^{\frac{\epsilon}{\epsilon-1}} \frac{\partial D}{\partial s} + D \frac{\epsilon}{\epsilon-1} \left[\delta^{1-\epsilon} \left(\frac{i}{s} \right)^{1-\epsilon} + \delta \right]^{\frac{\epsilon}{\epsilon-1}-1} (\epsilon-1)\delta^{1-\epsilon} \left(\frac{s}{i} \right)^{\epsilon-2} \left(\frac{1}{i} \right) &= -\rho l \delta^{\epsilon} \frac{s_l^{\epsilon-1}}{s^{\epsilon}} \\
\kappa \frac{\partial D}{\partial s} + D\epsilon \left[\delta^{1-\epsilon} \left(\frac{i}{s} \right)^{1-\epsilon} + \delta \right]^{\frac{1}{\epsilon-1}} \delta^{1-\epsilon} \left(\frac{s}{i} \right)^{\epsilon-2} \left(\frac{1}{i} \right) &= -\rho D \kappa \delta^{\epsilon} \frac{s_l^{\epsilon-1}}{s^{\epsilon}} \\
\frac{\partial D}{\partial s} + \underbrace{D\epsilon \left[\delta^{1-\epsilon} \left(\frac{i}{s} \right)^{1-\epsilon} + \delta \right]^{-1} \delta^{1-\epsilon} \left(\frac{s}{i} \right)^{\epsilon-2} \left(\frac{1}{i} \right)}_{\mathrm{A}} &= \underbrace{-\rho D \delta^{\epsilon} \frac{s_l^{\epsilon-1}}{s^{\epsilon}}}_{\mathrm{B}}
\end{aligned}
\tag{A.23}
$$

In order to simplify Equation A.23, we break it into two pieces as follows:

$$
-\frac{\partial D}{\partial s} \frac{s}{D} = \frac{s}{D}\mathrm{A} + \frac{s}{D}\mathrm{B} \tag{A.24}
$$

We first focus on **A**

$$
\begin{aligned}
\frac{s}{D}A &= \frac{s}{D}D\epsilon\left[\delta^{1-\epsilon}\left(\frac{i}{s}\right)^{1-\epsilon}+\delta\right]^{-1}\delta^{1-\epsilon}\left(\frac{s}{i}\right)^{\epsilon-2}\left(\frac{1}{i}\right)\\
&= \frac{s\epsilon\delta^{1-\epsilon}\left(\frac{s}{i}\right)^{\epsilon-1}\left(\frac{i}{s}\right)\left(\frac{1}{i}\right)}{\left[\delta^{1-\epsilon}\left(\frac{i}{s}\right)^{1-\epsilon}+\delta\right]}\\
&= \frac{\epsilon\delta^{1-\epsilon}\left(\frac{i}{s}\right)^{1-\epsilon}}{\left[\delta^{1-\epsilon}\left(\frac{i}{s}\right)^{1-\epsilon}+\delta\right]}\\
&= \left[\frac{1}{1+\delta^{\epsilon}\left(\frac{i}{s}\right)^{\epsilon-1}}\right]\epsilon
\end{aligned}
\tag{A.25}
$$

We then focus on **B**

$$
\begin{aligned}
\frac{s}{D}B &= \frac{s}{D}\rho D\delta^{\epsilon}\frac{s_l^{\epsilon-1}}{s^{\epsilon}}\\
&= \frac{s\rho\delta^{\epsilon}}{s^{\epsilon}(i^{1-\epsilon}+\delta^{\epsilon}s^{1-\epsilon})}\\
&= \frac{\rho\delta^{\epsilon}}{s^{\epsilon-1}i^{1-\epsilon}+\delta^{\epsilon}}\\
&= \frac{\rho\delta^{\epsilon}\left(\frac{i}{s}\right)^{\epsilon-1}}{\left(\frac{i}{s}\right)^{\epsilon-1}s^{\epsilon-1}i^{1-\epsilon}+\delta^{\epsilon}\left(\frac{i}{s}\right)^{\epsilon-1}}\\
&= \left[\frac{\delta^{\epsilon}\left(\frac{i}{s}\right)^{\epsilon-1}}{1+\left(\frac{i}{s}\right)^{\epsilon-1}}\right]\rho
\end{aligned}
\tag{A.26}
$$

After combining Equation A.25 and A.26, we get Equation 1.18

$$
-\frac{\partial D/D}{\partial s/s} = \left[\frac{1}{1+\delta^{\epsilon}(\frac{i}{s})^{\epsilon-1}}\right]\epsilon+\left[\frac{\delta^{\epsilon}(\frac{i}{s})^{\epsilon-1}}{1+\delta^{\epsilon}(\frac{i}{s})^{\epsilon-1}}\right]\rho
\tag{A.27}
$$

A.4 Deriving Campbell and Shiller (1988) (Equation 1.24)

This section outlines the decomposition proposed by Campbell and Ammer (1993) and Bernanke and Kuttner (2005) on unexpected stock returns. The holding period stock return H_{t+1} is given by the stock price P_t and any dividends D_t received.

$$1 + H_{t+1} = \frac{P_{t+1} + D_t}{P_t} \tag{A.28}$$

Taking logs on both sides and substituting h_{t+1} for $\ln(1+H_{t+1})$, we get:

$$h_{t+1} = ln(P_{t+1} + D_t) - ln(P_t) \tag{A.29}$$

Applying a log-linearization to $ln(P_{t+1} + Dt)$ and defining ρ as the steady state value of $\frac{P}{D+P}$, we can express the first difference as the weighted sum of the log differences:

$$\Delta ln(P_{t+1} + D_t) \approx \rho \Delta p_{t+1} + (1 - \rho)\Delta d_t \tag{A.30}$$

We can "integrate" this expression to get

$$ln(P_{t+1} + D_t) \approx k + \rho p_{t+1} + (1 - \rho) d_t \tag{A.31}$$

Substituting to Equation A.29 simplifies to:

$$\begin{aligned}
h_{t+1} &\approx k + \rho p_{t+1} + (1-\rho)d_t - p_t \\
&\approx k + \rho p_{t+1} + d_t - \rho d_t - p_t + \underbrace{\mathbf{d_{t-1} - p_t}}_{\delta_t} - \mathbf{d_{t-1}} + \mathbf{p_t} \\
&\approx k - \rho(d_t - p_{t+1}) + d_{t-1} - p_t + d_t - d_{t-1} \\
&\approx k - \rho(\delta_{t+1}) + \delta_t + \Delta d_t \\
h_{t+1} &\approx k + (1-\rho L^{-1})\delta_t + \Delta d_t
\end{aligned} \tag{A.32}$$

We can solve for δ_t as follows:

$$\begin{aligned}
\delta_t &= (1-\rho L^{-1})^{-1}(h_{t+1} - \Delta d_t - k) \\
&= \sum_{i=0}^{\infty} \rho^i (h_{t+1+i} - \Delta d_{t+i}) - \frac{k}{1-\rho}
\end{aligned} \tag{A.33}$$

Iterating forward one period gives:

$$\delta_{t+1} = \sum_{i=1}^{\infty} \rho^i (h_{t+1+i} - \Delta d_{t+i}) - \frac{k}{1-\rho} \tag{A.34}$$

A.5 Are FOMC Days Unique?

This paper studies how monetary policy surprises affect bank stock returns. However, it is important to address whether the effects work through the surprises or normal fluctuations of interest rates. Is it the case that bank stock returns respond the same way to monetary policy surprises as they do to interest rates?

If the effect of daily interest rate changes outside of FOMC days are similar to the results that I find on FOMC announcements using intradaily data, this suggests that only interest rate movements matter in explaining bank returns. However, if using interest rate changes outside of FOMC meetings yield different results, this suggests something unique about policy surprises. Because there are severe data limitations in studying intradaily changes of the eurodollar futures contracts on non-FOMC days, I use daily changes in Treasury yields starting from January 1984 to Decemnber 2017 to study bank stock returns on non-FOMC days. In order to justify that changes in Treasury yields are a good proxy, I first test whether bank returns on FOMC days using these changes provide similar results to my intradaily event study using the fourth eurodollars future contract. I run the following regression:

$$R_{i,t} = \beta_0 + \beta_1 \Delta i_t + \epsilon_{i,t} \tag{A.35}$$

where $R_{i,t}$ is the daily return of bank i's stock return on date t, Δi_t is the daily change in the 2, 5, and 10 Year Constant Maturity Treasury yield on date t. I estimate β_1 for both t during FOMC announcement days and during non-FOMC days.

The results for FOMC days is shown in Table A.1 where Panel (a) considers the period prior to the zero lower bound and Panel (b) during it. As Table A.1a shows, using changes in the two, five, and ten year Treasury results in a negative and statistically insignificant decline in bank stock returns. The magnitudes, however, are much smaller than the cross-sectional results of Table 1.3b with declines of 5 to 7 basis points. Moving forward into the zero-lower bound period in Table A.1b, we can see the similar reversal in coefficient sign. A 100 basis point increase in the 2 and 5 Year Treasury yield leads to a 57 and 28 basis point increase in bank stock returns, respectively. I now consider the same regression but on days in which there are no FOMC announcements. The results, shown in Table A.2, reveal that there is not the same robust reversal effect that we find on FOMC days. While there does exist such a switch using 10 Year Treasury yield changes, using the other two yields generate positive effects for bank stock returns both before and during the zero-lower bound period. These pooled regression results suggest that FOMC days yield different responses of bank stock returns to non-FOMC days and in particular, show that the reversal channel exists only on FOMC days.

In order to test whether these differences in sign are significant, I run the following time series regression:

$$R_{b,t} = \beta_0 + \beta_{0D} D_t + \beta_1 \Delta i_t + \beta_{1D} D_t \Delta i_t + \epsilon_{b,t} \tag{A.36}$$

where $R_{b,t}$ is the daily value-weighted return of the Bank Industry portfolio from Kenneth French's dataset, D_t is a dummy variable that is equal to one on FOMC days and 0 otherwise, and Δi_t are the daily changes in various Treasury yields. I'm interested in the significance of coefficient β_{1D} which tests whether there are significant differences in bank stock return sensitivities to yield changes between FOMC and non-FOMC days. I break the sample period into three parts: 1984-1996, 1997-2009 (pre-ZLB), and 2009-2015 (ZLB). The reason for this additional time period is because unconditionally, bank stock returns and changes in interest rates have been positively correlated since 1997 (See Figure A.1).

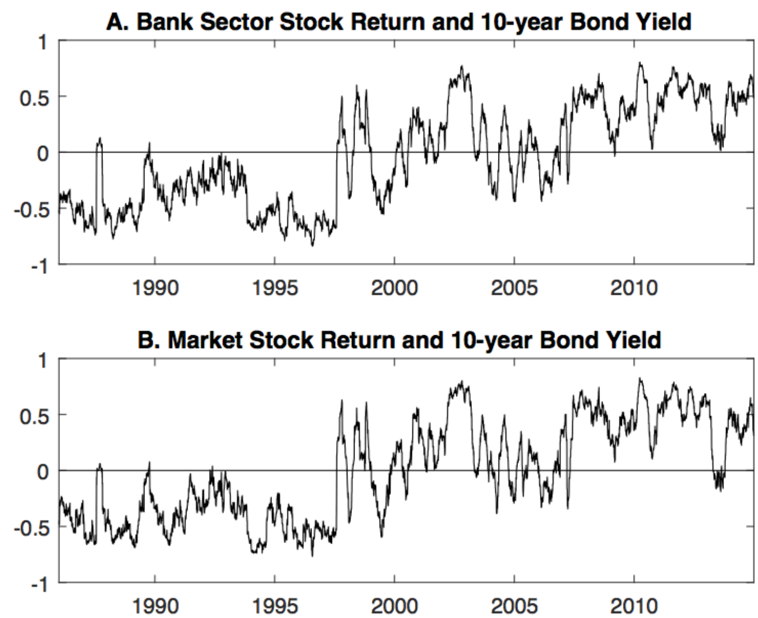


Figure A.1: Correlation Over Time

This figure plots the correlation between bank stock returns (Panel A) and the 10-year bond yield and the correlation between the market stock return and 10-year bond yield (Panel B).

The regression results for the three time periods are presented in Table A.3, Table A.4, and Table A.5 respectively. Table A.3 shows that there were no significant differences for bank return sensitivities to interest rate changes between FOMC and non-FOMC dates. Table A.4 and Table A.5, however, shows a negative and statistically significant coefficient of β_{1D} (shown in the red box), which suggests that on average, bank returns displayed a more negative sensitivity with respect to changes in Treasury yields on FOMC days than on non-FOMC days. For example, during the pre-ZLB period (Table A.4), a 1% increase in the 2-Year Treasury yield had a 5.5% larger negative effect on FOMC days relative to non-FOMC days. The negative coefficient on β_{1D} is consistent with the pooled regression and alludes to the fact that FOMC days are unique. It can perhaps be the case that on non-FOMC days, the positive effect of yields on bank returns is due in large part to a macroeconomic effect where a stronger economy is associated with higher yields and returns. Thus, it is especially difficult to disentangle the endogeneity between yields and returns. The negative effect that we find on actual FOMC days, however, could be related in large part to actual changes in the stance of monetary policy and speaks to the fact that higher yields are perceived as bad news for banks.

(a) Pre-ZLB Results

VARIABLES	(1) Daily Return (preZLB)	(2) Daily Return (preZLB)	(3) Daily Return (preZLB)
Δ 2-Year Treasury	-0.007		
	[0.005]		
Δ 5-Year Treasury		-0.007	
		[0.005]	
Δ 10-Year Treasury			-0.005
			[0.006]
Constant	0.002***	0.002***	0.002***
	[0.000]	[0.000]	[0.000]
Observations	41,203	41,203	41,203
R-squared	0.001	0.001	0.000
Cluster Date	Yes	Yes	Yes

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

(b) ZLB Results

VARIABLES	(1) Daily Return (ZLB)	(2) Daily Return (ZLB)	(3) Daily Return (ZLB)
Δ 2-Year Treasury	0.058***		
	[0.021]		
Δ 5-Year Treasury		0.029*	
		[0.015]	
Δ 10-Year Treasury			0.041**
			[0.017]
Constant	0.001	0.001	0.001
	[0.001]	[0.001]	[0.001]
Observations	7,234	7,234	7,234
R-squared	0.022	0.015	0.027
Cluster Date	Yes	Yes	Yes

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table A.1: The Response of Daily Bank Stock Returns to Changes in Treasury Yield on FOMC Days

The table reports the results of a regression of daily returns on FOMC meeting t for both the period before the zero lower bound (Panel A) and the period during the ZLB (Panel B). There are 537 banks in this sample. All variables are expressed in decimal form and are interpreted as the response of stock returns to a 100bp in the Treasury Yield. Column (1) uses the 2-Year Constant Maturity Treasury Yield, Column (2) uses the 5-Year Constant Maturity Treasury Yield, and Column (3) uses the 10-Year Constant Maturity Treasury Yield. Standard errors are clustered at the FOMC date level.

(a) Pre-ZLB Results

VARIABLES	(1) Daily Return (preZLB)	(2) Daily Return (preZLB)	(3) Daily Return (preZLB)
Δ 2-Year Treasury	0.003**		
	[0.001]		
Δ 5-Year Treasury		0.001	
		[0.001]	
Δ 10-Year Treasury			-0.002*
			[0.001]
Constant	0.001***	0.001***	0.001***
	[0.000]	[0.000]	[0.000]
Observations	1,347,135	1,347,135	1,347,135
R-squared	0.01	0.01	0.01
Cluster Date	Yes	Yes	Yes

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

(b) ZLB Results

VARIABLES	(1) Daily Return (ZLB)	(2) Daily Return (ZLB)	(3) Daily Return (ZLB)
Δ 2-Year Treasury	0.116***		
	[0.008]		
Δ 5-Year Treasury		0.081***	
		[0.005]	
Δ 10-Year Treasury			0.083***
			[0.004]
Constant	0.000**	0.000**	0.001***
	[0.000]	[0.000]	[0.000]
Observations	221,476	221,476	221,476
R-squared	0.032	0.047	0.058
Cluster Date	Yes	Yes	Yes

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table A.2: The Response of Daily Bank Stock Returns to Changes in Treasury Yield on non-FOMC Days

The table reports the results of a regression of daily returns on non-FOMC meeting t for both the period before the zero lower bound (Panel A) and the period during the ZLB (Panel B). There are 537 banks in this sample. All variables are expressed in decimal form and are interpreted as the response of stock returns to a 100bp in the Treasury Yield. Column (1) uses the 2-Year Constant Maturity Treasury Yield, Column (2) uses the 5-Year Constant Maturity Treasury Yield, and Column (3) uses the 10-Year Constant Maturity Treasury Yield. Standard errors are clustered at the RSSD level.

VARIABLES	(1) Banks	(2) Banks	(3) Banks
D_t	0.194	0.190	0.192
	[0.130]	[0.131]	[0.131]
Δ 2-Year Treasury	-3.654***		
	[0.250]		
$D_t \Delta$ 2-Year Treasury	$\boxed{-1.365}$		
	[1.299]		
Δ 5-Year Treasury		-4.245***	
		[0.218]	
$D_t \Delta$ 5-Year Treasury		$\boxed{-1.072}$	
		[1.403]	
Δ 10-Year Treasury			-4.618***
			[0.236]
$D_t \Delta$ 10-Year Treasury			$\boxed{-1.690}$
			[1.609]
Constant	0.064***	0.063***	0.063***
	[0.016]	[0.015]	[0.015]
Observations	2,636	2,636	2,636
R-squared	0.106	0.145	0.159

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table A.3: Daily Time Series Regression of 1984-1996

This table reports the results of estimating Equation A.36, a time series regression to test significance between FOMC meeting dates and non-FOMC meeting dates. D_t is a dummy variable that represents FOMC meeting dates. Column (1) uses the 2-Year Treasury yield, Column (2) uses the 5-Year Treasury yield, and Column (3) uses the 10-Year Treasury yield. Heteroskedasticity-consistent standard errors are reported in the bracket.

VARIABLES	(1) Banks	(2) Banks	(3) Banks
D_t	0.179	0.186	0.192
	[0.122]	[0.122]	[0.124]
Δ 2-Year Treasury	2.329***		
	[0.489]		
$D_t\Delta$ 2-Year Treasury	$\boxed{\text{-5.545***}}$		
	[1.742]		
Δ 5-Year Treasury		1.807***	
		[0.451]	
$D_t\Delta$ 5-Year Treasury		$\boxed{\text{-4.665**}}$	
		[1.828]	
Δ 10-Year Treasury			1.093**
			[0.480]
$D_t\Delta$ 10-Year Treasury			$\boxed{\text{-2.566}}$
			[2.407]
Constant	-0.005	-0.005	-0.005
	[0.024]	[0.025]	[0.025]
Observations	2,356	2,356	2,356
R-squared	0.017	0.012	0.004

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table A.4: Daily Time Series Regression of 1997-2009

This table reports the results of estimating Equation A.36, a time series regression to test significance between FOMC meeting dates and non-FOMC meeting dates. D_t is a dummy variable that represents FOMC meeting dates. Column (1) uses the 2-Year Treasury yield, Column (2) uses the 5-Year Treasury yield, and Column (3) uses the 10-Year Treasury yield. Heteroskedasticity-consistent standard errors are reported in the bracket.

VARIABLES	(1) Banks	(2) Banks	(3) Banks
D_t	0.019	0.070	0.049
	[0.167]	[0.176]	[0.174]
Δ 2-Year Treasury	13.689***		
	[0.977]		
$D_t\Delta$ 2-Year Treasury	$\boxed{-3.214}$		
	[3.838]		
Δ 5-Year Treasury		9.774***	
		[0.616]	
$D_t\Delta$ 5-Year Treasury		$\boxed{-6.035^{**}}$	
		[2.548]	
Δ 10-Year Treasury			9.973***
			[0.571]
$D_t\Delta$ 10-Year Treasury			$\boxed{-5.454^{**}}$
			[2.778]
Constant	0.075***	0.073***	0.079***
	[0.026]	[0.025]	[0.025]
Observations	1,653	1,653	1,653
R-squared	0.119	0.169	0.198

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table A.5: Daily Time Series Regression of 2009-2015 (ZLB)

This table reports the results of estimating Equation A.36, a time series regression to test significance between FOMC meeting dates and non-FOMC meeting dates. D_t is a dummy variable that represents FOMC meeting dates. Column (1) uses the 2-Year Treasury yield, Column (2) uses the 5-Year Treasury yield, and Column (3) uses the 10-Year Treasury yield. Heteroskedasticity-consistent standard errors are reported in the bracket.

A.6 Robustness Check: Identification by Heteroskedasticity

The seminal work by Rigobon and Sack (2004) addresses endogeneity concerns by defining a heteroskedasticity-based estimator of the response of asset prices to monetary policy. More specifically, it assumes that the variance of monetary policy shocks is higher on days of FOMC meetings and exploits this difference in volatility to measure the response of asset prices to monetary policy. While Rigobon and Sack (2004) proxies asset prices with the S&P 500 and NASDAQ, I focus again on Kenneth French's Bank industry portfolio and use daily changes in various Treasury yields. In addition to Equation A.35, Rigobon and Sack (2004) posits that interest rates also respond to developments in asset markets so that we have the following two equations.

$$\begin{aligned} R_{b,t} &= \alpha \Delta i_t + \eta_t \\ \Delta i_t &= \beta R_{b,t} + \epsilon_t \end{aligned} \tag{A.37}$$

Let $\Omega_{\mathcal{F}}$ and Ω_f denote the variance covariance matrix between treasury yields Δi_t and bank returns $R_{b,t}$ on FOMC days and non-FOMC days, respectively. In other words, $\Omega_{\mathcal{F}} = \mathrm{E}[[\Delta i_t R_{b,t}][\Delta i_t R_{b,t}]|t \in \mathcal{F}]$ and $\Omega_f = \mathrm{E}[[\Delta i_t R_{b,t}][\Delta i_t R_{b,t}]|t \in f]$. Our goal is to get an estimate of α and with some further assumptions, we can show that the difference in these covariance matrixes $\Delta\Omega = \Omega_{\mathcal{F}}$-$\Omega_f$ is given by

$$\Delta\Omega = \frac{\sigma_\epsilon^{\mathcal{F}} - \sigma_\epsilon^f}{(1-\alpha\beta)^2}\begin{bmatrix} 1 & \alpha \\ \alpha & \alpha^2 \end{bmatrix} \tag{A.38}$$

where σ_x^T represents the variance of shock x estimated using the sample $T \in \{\mathcal{F}, f\}$. In order to estimate α, I first define the following variables to include both FOMC and non-FOMC samples:

$$\begin{aligned} \Delta i &\equiv \{\Delta i_t, t \in \mathcal{F}\} \cup \{\Delta i_t, t \in f\} \\ R_b &\equiv \{R_{b,t}, t \in \mathcal{F}\} \cup \{R_{b,t}, t \in f\} \end{aligned} \tag{A.39}$$

where each are $(T_{\mathcal{F}} + T_f)$ x 1 vectors that include values of yield changes and bank returns both on FOMC days ($\mathcal{F}$) and non-FOMC days (f). In order to estimate α, the parameter of interest, I estimate a standard instrumental variables regression of R_b on Δi using as an instrument w_i, where

$$w_i \equiv \{\Delta i_t, t \in \mathcal{F}\} \cup \{-\Delta i_t, t \in f\} \tag{A.40}$$

This IV-regression yields the parameter of interest $\hat{\alpha}_{het}$, where

$$\hat{\alpha}_{het} = (w_i^{'}\Delta i)^{-1}(w_i^{'}R_b) \tag{A.41}$$

Table A.6 shows the coefficient $\hat{\alpha}_{het}$ which considers the heteroskedasticity of policy shocks on FOMC days. The first three rows correspond to the three sample periods I consider and shows that during 1984-1996, bank returns fell by 3.588% upon a 1% increase in the two-year treasury yield. It is interesting to note that during the period 1997-2009, bank portfolio returns increased along with interest rate rises which is surprising considering the fact that previous results suggest a negative relationship. When considering the entire pre-ZLB period (1984-2009), however, we see that bank returns decline by 1.312% upon a 100 basis point interest rate rise. During the zero-lower bound, however, we see a significant and positive increase of 14% of bank returns. While the magnitude is certainly large, Rigobon and Sack (2004) find an 11% decline using the NASDAQ index and a 7% decline using the S&P 500.

	Coef	Std Error	Observations	R-squared
1984-1996	-3.588***	0.225	2,636	0.105
1997-2009	2.737***	0.450	2,356	0.0090
2009-2015	13.968***	1.061	1,653	0.119
pre-ZLB (1984-2009)	-1.312***	0.229	4,991	0.0109
ZLB (2009-2015)	13.968***	1.061	1,653	0.119

*** p<0.01, ** p<0.05, * p<0.1

Table A.6: The Response of Bank Portfolio Return to Monetary Policy (Heteroskedasticity-Based Estimator)

This table reports the results of estimating the Rigobon and Sack (2004) instrumental variable regression of $\hat{\alpha_{het}}$ for the three periods: 1984-1996, 1997-2009, and 2009-2015 as well as prior to and during the zero-lower bound. The interest rate used in the regression is from the 2-Year Treasury.

APPENDIX A. APPENDIX TO CHAPTER 1

The results in this section suggest that FOMC days are certainly important when understanding the response of bank returns to monetary policy surprises. In order to better understand why bank returns reveal a reversal from prior to and during the zero-lower bound period and the characteristics that explain cross-sectional differences, I consider a model in which banks have market power and decide how much interest to charge borrowers and the interest to pay its depositors which is described in Section 1.5.

A.7 Data Appendix

Interest Earning Assets

Count	Call Report		RIS Data	Maturity	Type	FDIC File
1	RCFDA549	RCONA549	SCNM3LES	3mo or less	Govt	FTS
2	RCFDA550	RCONA550	SCNM3T12	3-12 months	Govt	
3	RCFDA551	RCONA551	SCNM1T3	1-3 years	Govt	
4	RCFDA552	RCONA552	SCNM3T5	3-5 years	Govt	
5	RCFDA553	RCONA553	SCNM5T15	5-15 years	Govt	
6	RCFDA554	RCONA554	SCNMOV15	over 15 years	Govt	
7	RCFDA555	RCONA555	SCPT3LES	3mo or less	Mortgage Pass Through	FTS
8	RCFDA556	RCONA556	SCPT3T12	3-12 months	Mortgage Pass Through	
9	RCFDA557	RCONA557	SCPT1T3	1-3 years	Mortgage Pass Through	
10	RCFDA558	RCONA558	SCPT3T5	3-5 years	Mortgage Pass Through	
11	RCFDA559	RCONA559	SCPT5T15	5-15 years	Mortgage Pass Through	
12	RCFDA560	RCONA560	SCPTOV15	over 15 years	Mortgage Pass Through	
13	RCFDA561	RCONA561	SCO3YLES	3 years or less	Other Mortgage-Backed Securities	FTS
14	RCFDA562	RCONA562	SCOOV3Y	over 3 years	Other Mortgage-Backed Securities	
15	RCONA564		LNRS3LES	3mo or less	Fixed/Float Rate Secured by first lien 1-4 family resid	FTS
16	RCONA565		LNRS3T12	3-12 months	Fixed/Float Rate Secured by first lien 1-4 family resid	
17	RCONA566		LNRS1T3	1-3 years	Fixed/Float Rate Secured by first lien 1-4 family resid	
18	RCONA567		LNRS3T5	3-5 years	Fixed/Float Rate Secured by first lien 1-4 family resid	
19	RCONA568		LNRS5T15	5-15 years	Fixed/Float Rate Secured by first lien 1-4 family resid	
20	RCONA569		LNRSOV15	over 15 years	Fixed/Float Rate Secured by first lien 1-4 family resid	
21	RCFD570	RCONA570	LNOT3LES	3mo or less	All other loans and leases (other than resid)	FTS
22	RCFD571	RCONA571	LNOT3T12	3-12 months	All other loans and leases (other than resid)	
23	RCFD572	RCONA572	LNOT1T3	1-3 years	All other loans and leases (other than resid)	
24	RCFD573	RCONA573	LNOT3T5	3-5 years	All other loans and leases (other than resid)	
25	RCFD574	RCONA574	LNOT5T15	5-15 years	All other loans and leases (other than resid)	
26	RCFD575	RCONA575	LNOTOV15	over 15 years	All other loans and leases (other than resid)	
TOTAL	RCFD2170	RCON2170	ASSET		Total Assets	FTS

Interest Paying Liabilities

Count	Call Report		RIS Data	Maturity	Type	FDIC File
1	RCON6810		NTRSMMDA		Money market deposit accounts held in domestic offices	FTS
2	RCON0352		NTRSOTH		All other savings deposits account (exclude mmda) held in d.o.	
3	RCONA579	RCONHK07	CD3LESS	3mo or less	Time Deposits $250K or less	FTS
4	RCONA580	RCONHK08	CD3T12S	3-12 months	Time Deposits $250K or less	
5	RCONA581	RCONHK09	CD1T3S	1-3 years	Time Deposits $250K or less	
6	RCONA582	RCONHK10	CDOV3S	over 3 years	Time Deposits $250K or less	
7	RCONA584	RCONHK12	CD3LES	3mo or less	Time Deposits OVER $250K	FTS
8	RCONA585	RCONHK13	CD3T12	3-12 months	Time Deposits OVER $250K	
9	RCONA586	RCONHK14	CD1T3	1-3 years	Time Deposits OVER $250K	
10	RCONA587	RCONHK15	CDOV3	over 3 years	Time Deposits OVER $250K	
11	RCON2215		TRN		Total Transaction Accounts held in domestic offices	FTS
TOTAL	RCFD2948	RCON2948	LIAB		Total Liabilities	FTS

Appendix B

Appendix to Chapter 2

B.1 Using Swanson (2017) Shocks

Building upon the framework of Gürkaynak et al. (2005) who posited that monetary policy can be represented by a target and path factor, Swanson (2017) includes an additional dimension of large scale asset purchases. This is done by first creating a $T \times n$ matrix called X of intradaily changes in asset prices where T is each FOMC announcement date and n are the changes. These changes include the federal funds futures (current and future six month), eurodollar futures (current and future eight quarters), Treasury bond yields (across various term structures), the stock market index, and exchange rates. Swanson (2017) then imposes a factor structure on X as follows:

$$X = F\Lambda + \epsilon \tag{B.1}$$

where F is a $T \times k$ matrix of unobserved factors, Λ is a $k \times n$ matrix of loadings (asset price response from factor k), and ϵ is a $T \times n$ matrix of residuals. Previous work by Gürkaynak et al. (2005) consider k=2, where intradaily asset price changes are well captured by two dimensions of monetary policy: changes in the target rate and the path of future policy (forward guidance). By imposing structure on Λ, Swanson (2017) is able to decompose monetary policy shocks into an additional third dimension related to large scale asset purchases[1]. Having these three dimensions (Target, FG, and LSAP), I estimate the following regression which is similar to Equation 2.5:

$$\begin{aligned} \Delta SPREAD_{t+1} &= \beta_0^s + \beta_1^s TARGET_{t+1} + \beta_2^s PATH_{t+1} + \beta_3^s LSAP_{t+1} + \epsilon_{t+1}^s \\ \Delta s_{t+1}^d &= \beta_0^d + \beta_1^d TARGET_{t+1} + \beta_2^d PATH_{t+1} + \beta_3^d LSAP_{t+1} + \epsilon_{t+1}^d \\ \Delta s_{t+1}^r &= \beta_0^r + \beta_1^r TARGET_{t+1} + \beta_2^r PATH_{t+1} + \beta_3^r LSAP_{t+1} + \epsilon_{t+1}^r \end{aligned} \tag{B.2}$$

[1] Derivations and details on this structure can be found in Section 2 of Swanson (2017).

(a) Full Sample Time Series Regression
August 1991 - October 2015

	(1) Spread	(2) Expected Default	(3) Risk Premium
Target Factor	-0.0304***	-0.00589***	-0.0213***
	(0.0106)	(0.00224)	(0.00736)
FG Factor	0.0104	0.00336	0.00592
	(0.0116)	(0.00258)	(0.00813)
LSAP Factor	0.0264	0.00723	0.0138
	(0.0335)	(0.00810)	(0.0204)
R^2	0.073	0.058	0.091
Observations	109	109	109

(b) Pre-ZLB Time Series Regression
August 1991 - December 2008

	(1) Spread	(2) Expected Default	(3) Risk Premium
Target Factor	-0.0285***	-0.00552**	-0.0207***
	(0.0108)	(0.00224)	(0.00748)
FG Factor	0.00186	0.00161	-0.000102
	(0.0113)	(0.00250)	(0.00808)
LSAP Factor	-0.0112	-0.00133	-0.00136
	(0.0299)	(0.00750)	(0.0200)
R^2	0.078	0.054	0.098
Observations	81	81	81

(c) ZLB Time Series Regression
January 2009 - December 2016

	(1) Spread	(2) Expected Default	(3) Risk Premium
Target Factor	0.368	0.0824	0.200
	(0.271)	(0.0694)	(0.155)
FG Factor	0.0860**	0.0191**	0.0557***
	(0.0358)	(0.00857)	(0.0206)
LSAP Factor	0.0982	0.0237	0.0477
	(0.0598)	(0.0147)	(0.0342)
R^2	0.369	0.324	0.380
Observations	28	28	28

Table B.1: Monthly Changes in Credit Spreads (and two components) Time Series Regression using Swanson (2017) Shocks

This table reports results from estimating Equation B.2 which regresses monthly change in credit spreads, expected default, and risk premium on $TARGET$, $PATH$, and $LSAP$. Column (1) reports the results for monthly changes in credit spreads, Column (2) for monthly changes in expected default, and Column (3) for monthly changes in risk premium. Panel B.1a presents the results the full sample from August 1991-October 2015, Panel B.1b presents the pre-ZLB sample from August 1991-December 2008, and Panel B.1c presents the ZLB sample from January 2009-October 2015. Standard errors are robust White standard errors.

B.2 Effect on Stock Returns

	(1) Full Sample 1984M2-2016M12	(2) Pre-ZLB 1984M2-2008M12	(3) ZLB 2009M1-2016M12
MP1	-0.0145	-0.0191	
	(0.0384)	(0.0386)	
PATH	-0.0888	-0.0859	-0.111
	(0.0649)	(0.0679)	(0.138)
Constant	0.00319	0.00113	0.00977
	(0.00289)	(0.00322)	(0.00640)
Observations	283	219	64
R^2	0.0290	0.0345	0.0112

Table B.2: Time Series Regression of Stock Returns

This table reports results from a time series regression of monthly stock returns on the sum of monetary policy surprises $MP1$ and $PATH$. Column (1) reports results for the full sample from February 1984 - December 2016, Column (2) for the Pre-ZLB period from February 1984 - December 2008, and Column (3) for the ZLB period from January 2009 - December 2016. Standard errors are robust White standard errors.

B.3 Model with Expected Default and Risk Premia

This section derives Merton (1974) using some adjustments described by Chen et al. (2008) to allow for the study of credit spreads and expected default. It is used to derive the comparative static relationship in Figure 2.1. I assume that asset values (V) follow a Geometric Brownian Motion under the natural measure (P) and risk neutral measure (Q).

$$\begin{aligned} \frac{dV_t}{V_t} &= (\mu - \delta)dt + \sigma dW_t^P \\ \frac{dV_t}{V_t} &= (r - \delta)dt + \sigma dW_t^Q \end{aligned} \tag{B.3}$$

where δ is the dividend yield, μ is the expected return on the firm's assets, r is the risk-free rate, and σ is asset volatility. I assume that a zero-coupon risky bond can only default at its maturity T and will occur if the value of its assets $V(T)$ fall below a certain threshold D which can be thought of as a debt level. However, like for most bonds, default does not completely wipe out the value of the firm and bond-holders are able to recover a fraction R which I assume to be constant. Therefore, the bond-holder has the following payoff:

$$\text{Payoff} = \begin{cases} \$1 & \text{if } V(T) > D \\ \$R & \text{if } V(T) < D \end{cases} \tag{B.4}$$

I now define the following:

$$v(t) = \log \underbrace{\left(\frac{V(t)}{D}\right)}_{\text{inverse-leverage}} \tag{B.5}$$

which can be interpreted as the inverse of **leverage** which is important for the study of different levels of risk. I apply Itô's Lemma to Equation B.5 which gives the following:

$$
\begin{aligned}
dv(t) &= \left(\mu - \delta - \frac{\sigma^2}{2}\right) dt + \sigma dw \\
dv(t) &= \left(r - \delta - \frac{\sigma^2}{2}\right) dt + \sigma dw^Q
\end{aligned} \tag{B.6}
$$

It then follows that $v(T)$ is normally distributed under both measures

$$
\begin{aligned}
v(T) &\sim N^P\left(v(0) + \left(\mu - \delta - \frac{\sigma^2}{2}\right) T, \sigma^2 T\right) \\
v(T) &\sim N^Q\left(v(0) + \left(r - \delta - \frac{\sigma^2}{2}\right) T, \sigma^2 T\right)
\end{aligned} \tag{B.7}
$$

From Equation B.5, it is clear that default will occur if $v(T) < 0$. Therefore, the P-measure probability (π^P) that the firm fails is:

$$
\begin{aligned}
\pi^P &= \frac{1}{\sqrt{2\pi\sigma^2 T}} \int_{-\infty}^{0} \exp\left[-\frac{1}{2\sigma^2 T}\left(v - v(0) - \left(\mu - \delta - \frac{\sigma^2}{2}\right) T\right)^2\right] dv \\
&= N\left[-\left(\frac{1}{\sqrt{\sigma^2 T}}\right)\left(\log\left(\frac{V_0}{D}\right) + \left(\mu - \delta - \frac{\sigma^2}{2}\right) T\right)\right] \\
\pi^Q &= N\left[-\left(\frac{1}{\sqrt{\sigma^2 T}}\right)\left(\log\left(\frac{V_0}{D}\right) + \left(r - \delta - \frac{\sigma^2}{2}\right) T\right)\right]
\end{aligned} \tag{B.8}
$$

The price of a zero-coupon risky bond maturing at T is equal to :

$$
P_{zc}^T = e^{-rT}\left[(1 - \pi^Q) + \pi^Q R\right] \tag{B.9}
$$

and if we write the price in terms of its yield, $P_{zc}^T = e^{-yT}$, we can solve for the credit spread as:

$$
\begin{aligned}
e^{-rT}\left[(1-\pi^Q)+\pi^Q R\right] &= e^{-yT} \\
rT - \log\ \left[(1-\pi^Q)+\pi^Q R\right] &= yT \\
\underbrace{y-r}_{\text{credit-spread}} &= \frac{1}{T}\log\left[1-(1-R)\pi^Q\right] \\
\underbrace{y^p-r}_{\text{expected-default}} &= \frac{1}{T}\log\left[1-(1-R)\pi^P\right] \\
\underbrace{y-y^p}_{\text{risk-premium}} &= \text{credit-spread} - \text{expected-default}
\end{aligned}
\tag{B.10}
$$

Appendix C

Appendix to Chapter 3

C.1 Details of Decomposition

C.1.1 Assumptions

- Recovery rate for the coupon upon default is the same as that of the principal

  –

$$\frac{C^f_{i,t}}{C_{i,t}} = exp(l_{it}) \tag{C.1}$$

- After default occurs, the investor buys Treasury bond with the coupon rate equal to the original coupon rate C_i and shorts the same bond so that the credit spreads and excess returns are always zero

C.1.2 Step 1: Write return to bond from t to $t+1$ as a function of bond's coupon

$$R_{i,t+1} = \frac{P_{i,t+1} + C_{i,t+1}}{P_{i,t}} \tag{C.2}$$

Multiply and divide right side by price-coupon ratio

$$\begin{aligned} R_{i,t+1} &= \frac{C_{i,t}}{P_{i,t}} \left(\frac{P_{i,t}}{C_{i,t}} \frac{P_{i,t+1} + C_{i,t+1}}{P_{i,t}} \right) \\ &= \frac{C_{i,t}}{P_{i,t}} \left(\frac{C_{i,t+1}}{C_{i,t}} + \frac{P_{i,t+1}}{C_{i,t}} \right) \\ &= \frac{C_{i,t}}{P_{i,t}} \frac{C_{i,t+1}}{C_{i,t}} \left(1 + \frac{P_{i,t+1}}{C_{i,t+1}} \right) \end{aligned}$$

Take logs, expressing logs in lower case:

$$r_{i,t+1} = c_{i,t} - p_{i,t} + \Delta c_{i,t+1} + log(1 + e^{p_{i,t+1} - c_{i,t+1}}) \tag{C.3}$$

C.1.3 Step 2: Linearize the return expression

$$r_{i,t+1} = -(p_{i,t} - c_{i,t}) + \Delta c_{i,t+1} + log(1 + e^{p_{i,t+1} - c_{i,t+1}}) \tag{C.4}$$

Taylor expand final term around mean log(P/C)

$$
\begin{aligned}
r_{i,t+1} &\approx -(p_{i,t} - c_{i,t}) + \Delta c_{i,t+1} + log(1 + e^{log(P/C)}) + \frac{1}{1 + e^{log(P/C)}} e^{log(P/C)} (p_{i,t+1} - c_{i,t+1} - log(P/C)) \\
&\approx -(p_{i,t} - c_{i,t}) + \Delta c_{i,t+1} + log(1 + e^{log(P/C)}) + \frac{P/C}{1 + P/C} (p_{i,t+1} - c_{i,t+1} - log(P/C))
\end{aligned}
$$

Collect constant terms, solve for $r_{i,t+1}$

$$
r_{i,t+1} \approx \frac{P/C}{1 + P/C} (p_{i,t+1} - c_{i,t+1} - log(P/C)) - (p_{i,t} - c_{i,t}) + \Delta c_{i,t+1} + log(1 + e^{log(P/C)})
$$

$$
r_{i,t+1} \approx \rho \delta_{i,t+1} - \delta_{i,t} + \Delta c_{i,t+1} + const
$$

where

- $\rho = \frac{P/C}{1+P/C}$
- $\delta_{i,t} = \log(\frac{P_{i,t}}{C_{i,t}})$

C.1.4 Step 3: Repeat for Treasury Bond

We know have:

$$
\begin{aligned}
r_{i,t+1} &\approx \rho \delta_{i,t+1} - \delta_{i,t} + \Delta c_{i,t+1} + const \\
r^f_{i,t+1} &\approx \rho \delta^f_{i,t+1} - \delta^f_{i,t} + \Delta c^f_{i,t+1} + const
\end{aligned}
$$

If we subtract the two, we get:

$$
r_{i,t+1} - r^f_{i,t+1} \approx -\rho(\delta^f_{i,t+1} - \delta_{i,t+1}) + (\delta^f_{i,t} - \delta_{i,t}) - (\Delta c^f_{i,t+1} - \Delta c_{i,t+1}) + const \quad \text{(C.5)}
$$

If we focus on the second term of the right hand side

$$\delta^f_{i,t} - \delta_{i,t} = \log \left(\frac{P^f_{i,t}}{P_{i,t}} \frac{C_{i,t}}{C^f_{i,t}} \right)$$

$$\delta^f_{i,t} - \delta_{i,t} = \begin{cases} \log \left(\frac{P^f_{i,t}}{P_{i,t}} \right) = s_{i,t} & \text{if } t \neq t_D \\ 0 & \text{if } t = t_D \end{cases}$$

If we focus on the last term on the right hand side and use the first assumption

$$\begin{aligned} (\Delta c^f_{i,t+1} - \Delta c_{i,t+1}) &= \log \left(\frac{C^f_{i,t+1}}{C_{i,t+1}} \frac{C_{i,t}}{C^f_{i,t}} \right) \\ &= \log \left(\frac{C^f_{i,t+1}}{C_{i,t+1}} \right) = l_{i,t+1} \end{aligned}$$

C.1.5 Step 4: Plug in all Equations

$$r^e_{i,t+1} = \log\left(R_{i,t+1}\right) - \log\left(R^f_{i,t+1}\right) \approx -\rho s_{i,t+1} + s_{i,t} - l_{i,t+1} + const \tag{C.6}$$

This decomposition has no term that involves coupon rates $C_{i,t}$ or $C^f_{i,t}$ because the coupon rates are equal and cancel out.

C.1.6 Step 5: Solve the Difference Equation

$$
\begin{aligned}
r^e_{i,t+1} &\approx -\rho s_{i,t+1} + s_{i,t} - l_{i,t+1} + const \\
s_{i,t} &\approx r^e_{i,t+1} + \rho s_{i,t+1} + l_{i,t+1} + const \\
s_{i,t+1} &\approx r^e_{i,t+2} + \rho s_{i,t+2} + l_{i,t+2} + const \\
s_{i,t} &\approx r^e_{i,t+1} + \rho(r^e_{i,t+2} + \rho s_{i,t+2} + l_{i,t+2}) + l_{i,t+1} + const \\
s_{i,t} &\approx \sum_{j=1}^{T_i-t} \rho^{j-1} r^e_{i,t+j} + \sum_{j=1}^{T_i-t} \rho^{j-1} l_{i,t+j} + const
\end{aligned}
$$

Since this holds path-by-path, it must also hold under expectations.

C.2 Data

C.2.1 Corporate Bond Database

In this section, we provide a more detailed description of the panel data of corporate bond prices by following the methodology of Nozawa (2017). We obtain monthly price observations of senior unsecured corporate bonds from the following four data sources. For the period from 1973 to 1997, we use the *Lehman Brothers Fixed Income Database*, which provides month-end bid prices. Since Lehman Brothers used these prices to construct the Lehman Brothers bond index while simultaneously trading it, the traders at Lehman Brothers had an incentive to provide correct quotes. Thus, although the prices in the *Lehman Brothers Fixed Income Database* are quote-based, they are considered reliable.

In the *Lehman Brothers Fixed Income Database*, some observations are dealers' quotes while others are matrix prices. Matrix prices are set using algorithms based on the quoted prices of other bonds with similar characteristics. Though matrix prices are less reliable than actual dealer quotes (Warga and Welch (1993)), we choose to include matrix prices in our main result to maximize the power of the test.

Second, for the period from 1994 to 2014, we use the *Mergent FISD/NAIC Database*. This database consists of actual transaction prices reported by insurance companies. Third, for the period from 2002 to 2014, we use *TRACE* data, which provides actual transaction prices. *TRACE* covers more than 99% of the OTC activities in U.S. corporate bond markets after 2005. The data from *Mergent FISD/NAIC* and *TRACE* are transaction-based data, and therefore the observations are not exactly at the end of months. Thus, we use only observations that are in the last five days of each month. If there are multiple observations in the last five days, we use the latest one and treat it as a month-end observation. Fourth, we use the *DataStream* database, which provides month-end price quotes from 1990 to 2011. Lastly, we use the *Merrill Lynch* database which provides month-end quotes from 1998 to 2014.

TRACE includes some observations from the trades that are eventually cancelled or corrected. We drop all cancelled observations, and use the corrected prices for the trades that are corrected. We also drop all the price observations that include dealer commissions, as the commission does not reflect the value of the bond, and these prices are not comparable to prices without commissions.

Since there are some overlaps among the five databases, we prioritize in the following order: the *Lehman Brothers Fixed Income Database*, *TRACE*, *Mergent FISD/NAIC* , *DataStream* and *Merrill Lynch*. To classify the bonds based on credit ratings, we use the ratings of Standard & Poor's when available, and use Moody's ratings when Standard & Poor's rating is not available.

To identify defaults in the data, we use *Moody's Default and Recovery Database*, which provides a historical record of bond defaults from 1970 onwards. The same source also provides the secondary-market value of the defaulted bond one month after the incident. If the price observation in the month when a bond defaults is missing in the corporate bond database, we add the Moody's secondary-market price to our data set in order to include all default observations in the sample.

C.2.2 Constructing Monetary Policy Shocks

As mentioned in the paper, we use two proxies for monetary policy shocks: the current month surprise in the federal funds rate futures contract (MP1) for the pre-ZLB period and the fourth eurodollar futures contract (ED4) in the ZLB period. While ED4 is simply the intradaily change in that contract around the FOMC meeting, the construction of MP1, which relies on the effective federal funds rate, requires scaling for the amount of days in a particular month. The settlement price for a federal funds rate futures contract is based on the monthly average federal funds rate [1]. In order to construct MP1, we need to consider the fact that part of the month has already passed prior to the FOMC meeting. Suppose there are D days in the month and the FOMC meeting occurs on day d of month m. Let $f^1_{t-\Delta t}$ be the price of the current month's federal funds rate futures contract ten minutes before the FOMC meeting and let f^1_t be the price twenty minutes after the meeting. Also, let $r_{m,-1}$ be the average federal funds rate in month m up until the announcement and $r_{m,0}$ the average federal funds rate in month m for the remainder of the month following the announcement. We then have the following relationship:

$$
\begin{aligned}
f^1_{t-\Delta t} &= \frac{d_0}{m_0} r_{m,-1} + \frac{m_0 - d_0}{m_0} E_{t-\Delta t} r_{m,0} \\
f^1_t &= \frac{d_0}{m_0} r_{m,-1} + \frac{m_0 - d_0}{m_0} E_t r_{m,0} \\
\underbrace{E_t r_0 - E_{t-\Delta t} r_0}_{MP1} &= \frac{m_0}{m_0 - d_0} \left[f^1_t - f^1_{t-\Delta t} \right]
\end{aligned}
$$

For example, on the FOMC meeting that occurred on 9/21/2011, we compute the intradaily change in the futures contract as 0.0025. In order to compute MP1, the monetary policy shock on that day, we multiply 0.0025 by the scaled factor $\frac{30}{30-21}$ which is equal to 0.00834. One notable exception is if there is a meeting at the end of the month. In this case, MP1 is equal the intradaily change that occurs next month.

[1] Federal funds rate futures contracts have been traded since 1988 and the effective rate is quoted by the Federal Reserve Bank of New York every business day

For example, on the FOMC meeting that occurred on 10/29/2014, we assign the intradaily change that month as 0 but set MP1 = 0.005, the intradaily change of the two month ahead federal funds futures contract.

C.2.3 Firm Balance Sheet

In order to attain firm balance sheet information (Compustat) for each bond (CRSP), we need to match identifiers in both data bases. For each bond, we use a linking table between CRSP identified by its *PERMNO* and Compustat identified by its *GVKEY*. There may, however, be duplicate matches in which one *PERMNO* correspond to multiple *GVKEY*s. When this occurs, we resort to the *linktype* variable in the table which describes how well a match exists. We keep those whose value corresponds to *LC* (Link Research Complete) and remove those of *LD* (Duplicate Link) and *LX* (Link to a security traded on another exchange not included in CRSP). This initial *PERMNO-CRSP* match results in 937,286 bond-date observations.

Daily prices and shares outstanding come from CRSP and is matched seamlessly with the bond's *PERMNO*. After deleting missing prices, we are left with 648,657 bond-date observations. In order to complete the match on firm balance sheet information, we turn to quarterly Compustat data. In order to match monthly bond data with quarterly balance sheet data, we first take an average across months to generate 89,583 quarterly data of a firm's price, shares outstanding, credit spread and its two components, maturity, and its rating.

C.2.4 Data Construction

We winsorize and trim all the balance sheet data at the 2nd and 98th percentile level, follow various authors on data construction, and describe them in detail below:

1. Investment (Ottonello and Winberry (2018)): $\Delta\log\, k_{i,t+1}$, where $k_{i,t}$ denotes the capital stock of firm i in quarter t. We initialize $k_{i,t}$ as the first reported value on the level of gross property, plant, and equipment (`ppegtq`). For subsequent periods, we compute the evolution of $k_{i,t+1}$ as the sum of $k_{i,t}$ and changes in the net property, plant, and equipment (`ppentq`) which has significantly more observations. We linearly interpolate missing values of `ppentq` if it is between two non-missing values. Finally, we compute investment as the change in log capital ($\Delta\log\, k_{i,t+1}$) and require firms to have at least 30 quarters of investment. Gross investment (`ppegtq`) is not used because there are much fewer observations than net investment.

2. Market Equity: *me* is equal to the product of price (`prc`) and shares outstanding (`shrout`) from CRSP

3. Book Equity (Hou et al. (2015)): *be* is shareholders' equity plus deferred and investment tax credit (`TXDITCQ`) minus the book value of preferred stock (`PSTKQ`). For shareholders' equity, we define it in the following order. First, we use stockholders' equity (`SEQQ`). Second, if that is unavailable, we define it as common equity (`CEQQ`) plus the book value of preferred stock (`PSTKQ`). Finally, if the

above two are still unavailable, we define it as total assets (`ATQ`) minus total liabilities (`LTQ`).

4. Leverage (Ottonello and Winberry (2018)) : *lev* is the ratio of total debt - debt in current liabilities (`DLCQ`) and long term debt (`DLTTQ`) to total assets (`ATQ`).

5. Sales Growth : *sales_growth* is the change in log sales (`SALEQ`)

C.3 Empirical Results

Different Horizons

	(1) Full Sample 1984Q1-2016Q4	(2) Pre-ZLB 1984Q1-2008Q4	(3) ZLB 2009Q1-2016Q4
MP1	0.0234	0.0275	
	(0.0162)	(0.0173)	
$s^d \times MP1$	0.0433**	0.0354**	
	(0.0171)	(0.0158)	
$s^r \times MP1$	-0.0663***	-0.0542***	
	(0.0207)	(0.0195)	
ED4			-0.0793***
			(0.0281)
$s^d \times ED4$			-0.00161
			(0.0232)
$s^r \times ED4$			0.000249
			(0.0259)
Constant	0.0347***	0.0442***	0.0210**
	(0.00434)	(0.00571)	(0.00813)
Coefficient Sum	$\boxed{-0.0230}$	$\boxed{-0.0188}$	$\boxed{-0.00136}$
SE Sum	0.00860	0.00882	0.0153
t-stat	-2.671	-2.128	-0.0890
Observations	24513	16971	7542
R^2	0.0259	0.0298	0.0254
Controls	Yes	Yes	Yes

Table C.1: Heterogeneity of Transmission Mechanism using $\Delta k_{i,t}$

Results from estimating Equation 3.12 using sample of non-financial firms that are matched to bonds. Column (1) reports estimates using the full sample (1984Q1-2016Q4), Column (2) reports from the Pre-ZLB period (1984Q1-2008Q4), and Column (3) the period during the zero-lower bound (2009Q1-2016Q4). MP1 is the surprise component in the current month federal funds rate futures contract scaled by the number of days relative to the FOMC meeting. ED4 is the surprise component of the fourth eurodollar futures contract. Both shocks are normalized so that positive values correspond to expansionary shocks (decrease in interest rates). s^d and s^r are standardized to have mean 0 and standard deviation of 1. For more details on the construction of MP1 and ED4, see Gürkaynak et al. (2005) and Appendix C.2.2. Firm controls include book to market ratio, leverage, sales growth, size, and current assets as a share of total assets. Aggregate controls include GDP growth rate, unemployment rate, and inflation. Standard errors are clustered by quarters.

	(1) Full Sample 1984Q1-2016Q4	(2) Pre-ZLB 1984Q1-2008Q4	(3) ZLB 2009Q1-2016Q4
MP1	0.00657	0.00516	
	(0.0125)	(0.0119)	
$s^d \times MP1$	0.0282	0.0193	
	(0.0174)	(0.0156)	
$s^r \times MP1$	-0.0500**	-0.0386**	
	(0.0211)	(0.0193)	
ED4			0.00461
			(0.0312)
$s^d \times ED4$			-0.0177
			(0.0203)
$s^r \times ED4$			-0.00352
			(0.0335)
Constant	0.0435***	0.0577***	0.0137*
	(0.00479)	(0.00580)	(0.00797)
Coefficient Sum	$\boxed{-0.0218}$	$\boxed{-0.0193}$	$\boxed{-0.0212}$
SE Sum	0.0110	0.0108	0.0209
t-stat	-1.977	-1.784	-1.014
Observations	23348	16325	7023
R^2	0.0216	0.0296	0.0153
Controls	Yes	Yes	Yes

Table C.2: Heterogeneity of Transmission Mechanism using $\Delta k_{i,t+1}$

Results from estimating Equation 3.12 using sample of non-financial firms that are matched to bonds. Column (1) reports estimates using the full sample (1984Q1-2016Q4), Column (2) reports from the Pre-ZLB period (1984Q1-2008Q4), and Column (3) the period during the zero-lower bound (2009Q1-2016Q4). MP1 is the surprise component in the current month federal funds rate futures contract scaled by the number of days relative to the FOMC meeting. ED4 is the surprise component of the fourth eurodollar futures contract. Both shocks are normalized so that positive values correspond to expansionary shocks (decrease in interest rates). s^d and s^r are standardized to have mean 0 and standard deviation of 1. For more details on the construction of MP1 and ED4, see Gürkaynak et al. (2005) and Appendix C.2.2. Firm controls include book to market ratio, leverage, sales growth, size, and current assets as a share of total assets. Aggregate controls include GDP growth rate, unemployment rate, and inflation. Standard errors are clustered by quarters.

	(1) Full Sample 1984Q1-2016Q4	(2) Pre-ZLB 1984Q1-2008Q4	(3) ZLB 2009Q1-2016Q4
MP1	-0.0168	-0.0196	
	(0.0192)	(0.0207)	
$s^d \times MP1$	0.0240	0.0162	
	(0.0157)	(0.0147)	
$s^r \times MP1$	-0.0331	-0.0229	
	(0.0221)	(0.0208)	
ED4			-0.00596
			(0.0588)
$s^d \times ED4$			0.0146
			(0.0281)
$s^r \times ED4$			-0.0462
			(0.0366)
Constant	0.0433***	0.0552***	0.0154*
	(0.00445)	(0.00601)	(0.00806)
Coefficient Sum	$\boxed{-0.00908}$	$\boxed{-0.00667}$	$\boxed{-0.0316}$
SE Sum	0.0110	0.0112	0.0159
t-stat	-0.826	-0.594	-1.982
Observations	22281	15686	6595
R^2	0.0242	0.0327	0.0199
Controls	Yes	Yes	Yes

Table C.3: Heterogeneity of Transmission Mechanism using $\Delta k_{i,t+2}$

Results from estimating Equation 3.12 using sample of non-financial firms that are matched to bonds. Column (1) reports estimates using the full sample (1984Q1-2016Q4), Column (2) reports from the Pre-ZLB period (1984Q1-2008Q4), and Column (3) the period during the zero-lower bound (2009Q1-2016Q4). MP1 is the surprise component in the current month federal funds rate futures contract scaled by the number of days relative to the FOMC meeting. ED4 is the surprise component of the fourth eurodollar futures contract. Both shocks are normalized so that positive values correspond to expansionary shocks (decrease in interest rates). s^d and s^r are standardized to have mean 0 and standard deviation of 1. For more details on the construction of MP1 and ED4, see Gürkaynak et al. (2005) and Appendix C.2.2. Firm controls include book to market ratio, leverage, sales growth, size, and current assets as a share of total assets. Aggregate controls include GDP growth rate, unemployment rate, and inflation. Standard errors are clustered by quarters.

	(1) Full Sample 1984Q1-2016Q4	(2) Pre-ZLB 1984Q1-2008Q4	(3) ZLB 2009Q1-2016Q4
MP1	-0.0210	-0.0254	
	(0.0158)	(0.0160)	
$s^d \times MP1$	0.00725	-0.0000995	
	(0.0139)	(0.0130)	
$s^r \times MP1$	-0.0228	-0.0145	
	(0.0145)	(0.0137)	
ED4			0.00657
			(0.0656)
$s^d \times ED4$			0.00434
			(0.0197)
$s^r \times ED4$			0.00135
			(0.0298)
Constant	0.0416***	0.0530***	0.0105
	(0.00461)	(0.00636)	(0.0102)
Coefficient Sum	$\boxed{-0.0156}$	$\boxed{-0.0146}$	$\boxed{0.00569}$
SE Sum	0.00744	0.00737	0.0203
t-stat	-2.093	-1.985	0.280
Observations	21582	15267	6315
R^2	0.0226	0.0290	0.0221
Controls	Yes	Yes	Yes

Table C.4: Heterogeneity of Transmission Mechanism using $\Delta k_{i,t+3}$

Results from estimating Equation 3.12 using sample of non-financial firms that are matched to bonds. Column (1) reports estimates using the full sample (1984Q1-2016Q4), Column (2) reports from the Pre-ZLB period (1984Q1-2008Q4), and Column (3) the period during the zero-lower bound (2009Q1-2016Q4). MP1 is the surprise component in the current month federal funds rate futures contract scaled by the number of days relative to the FOMC meeting. ED4 is the surprise component of the fourth eurodollar futures contract. Both shocks are normalized so that positive values correspond to expansionary shocks (decrease in interest rates). s^d and s^r are standardized to have mean 0 and standard deviation of 1. For more details on the construction of MP1 and ED4, see Gürkaynak et al. (2005) and Appendix C.2.2. Firm controls include book to market ratio, leverage, sales growth, size, and current assets as a share of total assets. Aggregate controls include GDP growth rate, unemployment rate, and inflation. Standard errors are clustered by quarters.

Bibliography

Aharony, Joseph, Anthony Saunders, and Ithzak Swary, "The effects of a shift in monetary policy regime on the profitability and risk of commercial banks," *Journal of Monetary Economics*, 1986, *17* (3), 363–377.

Akella, Srinivas R and Stuart I Greenbaum, "Innovations in interest rates, duration transformation, and bank stock returns," *Journal of Money, Credit and Banking*, 1992, *24* (1), 27–42.

Ampudia, Miguel and Skander Van den Heuvel, "Monetary policy and bank equity values in a time of low interest rates," 2017.

Arai, Natsuki, "The effects of monetary policy announcements at the zero lower bound," *International Journal of Central Banking*, 2017, *13* (2), 159–196.

Bae, Sung C, "Interest rate changes and common stock returns of financial institutions: revisited," *Journal of Financial Research*, 1990, *13* (1), 71–79.

Begenau, Juliane, Monika Piazzesi, and Martin Schneider, "Banks' risk exposures," Technical Report, National Bureau of Economic Research 2015.

Bernanke, Ben S and Alan S Blinder, "The Federal Funds Rate and the Channels of Monetary Transmission," *The American Economic Review*, 1992, *82* (4), 901–921.

_ and Kenneth N Kuttner, "What explains the stock market's reaction to Federal Reserve policy?," *The Journal of finance*, 2005, *60* (3), 1221–1257.

_ and Mark Gertler, "Inside the black box: the credit channel of monetary policy transmission," *Journal of Economic perspectives*, 1995, *9* (4), 27–48.

_ , _ , and Simon Gilchrist, "The financial accelerator in a quantitative business cycle framework," *Handbook of macroeconomics*, 1999, *1*, 1341–1393.

Bernanke, Ben, Vincent Reinhart, and Brian Sack, "Monetary policy alternatives at the zero bound: An empirical assessment," *Brookings Papers on Economic Activity*, 2004, *2004* (2), 1–100.

Bongaerts, Dion et al., *Overrated credit risk: three essays on credit risk in turbulent times* 2010.

Borio, Claudio and Haibin Zhu, "Capital regulation, risk-taking and monetary policy: a missing link in the transmission mechanism?," *Journal of Financial Stability*, 2012, *8* (4), 236–251.

Bredin, Don, Stuart Hyde, Dirk Nitzsche, and Gerard O'reilly, "UK stock returns and the impact of domestic monetary policy shocks," *Journal of Business Finance & Accounting*, 2007, *34* (5-6), 872–888.

Brunnermeier, Markus K and Yann Koby, "The reversal interest rate: An effective lower bound on monetary policy," 2018.

Campbell, Jeffrey R, Charles L Evans, Jonas DM Fisher, Alejandro Justiniano, Charles W Calomiris, and Michael Woodford, "Macroeconomic effects of federal reserve forward guidance [with comments and discussion]," *Brookings Papers on Economic Activity*, 2012, pp. 1–80.

Campbell, John Y and John Ammer, "What moves the stock and bond markets? A variance decomposition for long-term asset returns," *The Journal of Finance*, 1993, *48* (1), 3–37.

_ **and Robert J Shiller**, "The dividend-price ratio and expectations of future dividends and discount factors," *The Review of Financial Studies*, 1988, *1* (3), 195–228.

_ **and** _ , "Stock prices, earnings, and expected dividends," *The Journal of Finance*, 1988, *43* (3), 661–676.

Chen, Long, Pierre Collin-Dufresne, and Robert S Goldstein, "On the relation between the credit spread puzzle and the equity premium puzzle," *The Review of Financial Studies*, 2008, *22* (9), 3367–3409.

Chodorow-Reich, Gabriel, "Effects of unconventional monetary policy on financial institutions," Technical Report, National Bureau of Economic Research 2014.

Christiano, Lawrence J, Martin Eichenbaum, and Charles L Evans, "Nominal rigidities and the dynamic effects of a shock to monetary policy," *Journal of Political Economy*, 2005, *113* (1), 1–45.

Cochrane, John H, "The New-Keynesian Liquidity Trap," Technical Report, National Bureau of Economic Research 2013.

Collin-Dufresn, Pierre, Robert S Goldstein, and J Spencer Martin, "The determinants of credit spread changes," *The Journal of Finance*, 2001, *56* (6), 2177–2207.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, "The deposits channel of monetary policy," *The Quarterly Journal of Economics*, 2017, *132* (4), 1819–1876.

Duffee, Gregory R, "The relation between treasury yields and corporate bond yield spreads," *The Journal of Finance*, 1998, *53* (6), 2225–2241.

DAmico, Stefania and Thomas B King, "Flow and stock effects of large-scale treasury purchases: Evidence on the importance of local supply," *Journal of Financial Economics*, 2013, *108* (2), 425–448.

Ehrmann, Michael and Marcel Fratzscher, "Taking stock: Monetary policy transmission to equity markets," 2004.

Elsaify, Amora and Nikolai Roussanov, "Why Do Firms Issue Callable Bonds?," 2016.

Elton, Edwin J, Martin J Gruber, Deepak Agrawal, and Christopher Mann, "Explaining the rate spread on corporate bonds," *The Journal of Finance*, 2001, *56* (1), 247–277.

English, William B, Skander J Van den Heuvel, and Egon Zakrajšek, "Interest rate risk and bank equity valuations," *Journal of Monetary Economics*, 2018, *98*, 80–97.

_ , _ , and _ , "Interest rate risk and bank equity valuations," *Journal of Monetary Economics*, 2018.

Flannery, Mark J and Christopher M James, "The effect of interest rate changes on the common stock returns of financial institutions," *The Journal of Finance*, 1984, *39* (4), 1141–1153.

Gertler, Mark and Peter Karadi, "A model of unconventional monetary policy," *Journal of Monetary Economics*, 2011, *58* (1), 17–34.

_ and _ , "Monetary policy surprises, credit costs, and economic activity," *American Economic Journal: Macroeconomics*, 2015, *7* (1), 44–76.

_ and Simon Gilchrist, "Monetary policy, business cycles, and the behavior of small manufacturing firms," *The Quarterly Journal of Economics*, 1994, *109* (2), 309–340.

Gilchrist, Simon and Egon Zakrajšek, "Credit spreads and business cycle fluctuations," *American Economic Review*, 2012, *102* (4), 1692–1720.

_ , David López-Salido, and Egon Zakrajšek, "Monetary policy and real borrowing costs at the zero lower bound," *American Economic Journal: Macroeconomics*, 2015, *7* (1), 77–109.

Gurkaynak, Refet S, Brian P Sack, and Eric T Swanson, "Do actions speak louder than words? The response of asset prices to monetary policy actions and statements," 2004.

Gürkaynak, Refet S, Brian Sack, and Eric T Swansonc, "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*, 2005.

Hanson, Samuel G and Jeremy C Stein, "Monetary policy and long-term real rates," *Journal of Financial Economics*, 2015, *115* (3), 429–448.

Hodrick, Robert J, "Dividend yields and expected stock returns: Alternative procedures for inference and measurement," *The Review of Financial Studies*, 1992, *5* (3), 357–386.

Hou, Kewei, Chen Xue, and Lu Zhang, "Digesting anomalies: An investment approach," *The Review of Financial Studies*, 2015, *28* (3), 650–705.

Huang, Jing-Zhi and Ming Huang, "How much of the corporate-treasury yield spread is due to credit risk?," *The Review of Asset Pricing Studies*, 2012, *2* (2), 153–202.

Jordà, Òscar, "Estimation and inference of impulse responses by local projections," *American Economic Review*, 2005, *95* (1), 161–182.

Kashyap, Anil K and Jeremy C Stein, "The impact of monetary policy on bank balance sheets," in "Carnegie-Rochester Conference Series on Public Policy," Vol. 42 Elsevier 1995, pp. 151–195.

_ **, Owen A Lamont, and Jeremy C Stein**, "Credit conditions and the cyclical behavior of inventories," *The Quarterly Journal of Economics*, 1994, *109* (3), 565–592.

Kiley, Michael T, "Monetary policy statements, treasury yields, and private yields: before and after the zero lower bound," *Finance Research Letters*, 2016, *18*, 285–290.

Kontonikas, Alexandros, Charles Nolan, Zivile Zekaite et al., "Always and everywhere inflation? Treasuries variance decomposition and the impact of monetary policy," Technical Report 2015.

Krishnamurthy, Arvind and Annette Vissing-Jorgensen, "The aggregate demand for treasury debt," *Journal of Political Economy*, 2012, *120* (2), 233–267.

Kuttner, Kenneth N, "Monetary policy surprises and interest rates: Evidence from the Fed funds futures market," *Journal of monetary economics*, 2001, *47* (3), 523–544.

Kwan, Simon H, "Re-examination of interest rate sensitivity of commercial bank stock returns using a random coefficient model," *Journal of Financial Services Research*, 1991, *5* (1), 61–76.

Longstaff, Francis A and Eduardo S Schwartz, "A simple approach to valuing risky fixed and floating rate debt," *The Journal of Finance*, 1995, *50* (3), 789–819.

Merton, Robert C, "On the pricing of corporate debt: The risk structure of interest rates," *The Journal of finance*, 1974, *29* (2), 449–470.

Modigliani, Franco and Merton H. Miller, "The Cost of Capital, Corporation Finance and the Theory of Investment," *The American Economic Review*, 1958, *48* (3), 261–297.

Nakamura, Emi and Jón Steinsson, "High frequency identification of monetary non-neutrality: The information effect," *Quarterly Journal of Economics*, 2018.

Nozawa, Yoshio, "What Drives the Cross-Section of Credit Spreads?: A Variance Decomposition Approach," *The Journal of Finance*, 2017, *72* (5), 2045–2072.

Oliner, Stephen D and Glenn D Rudebusch, "Is there a broad credit channel for monetary policy?," *Economic Review - Federal Reserve Bank of San Francisco*, 1996, *1*, 3–13.

Ottonello, Pablo and Thomas Winberry, "Financial Heterogeneity and the Investment Channel of Monetary Policy," Technical Report, National Bureau of Economic Research 2018.

Owyang, Michael T and Garey Ramey, "Regime switching and monetary policy measurement," *Journal of Monetary Economics*, 2004, *51* (8), 1577–1597.

Ramey, Valerie A, "Macroeconomic shocks and their propagation," in "Handbook of macroeconomics," Vol. 2, Elsevier, 2016, pp. 71–162.

Raskin, Matthew, "The Financial Market Effects of Unconventional Monetary Policy." PhD dissertation, The Johns Hopkins University 2014.

Rigobon, Roberto and Brian Sack, "Measuring the reaction of monetary policy to the stock market," *The quarterly journal of Economics*, 2003, *118* (2), 639–669.

— **and** — , "The impact of monetary policy on asset prices," *Journal of Monetary Economics*, 2004, *51* (8), 1553–1575.

Romer, Christina D and David H Romer, "Federal Reserve information and the behavior of interest rates," *American Economic Review*, 2000, *90* (3), 429–457.

Santos, Joao AC, "Bank capital regulation in contemporary banking theory: A review of the literature," *Financial Markets, Institutions & Instruments*, 2001, *10* (2), 41–84.

Swanson, Eric T, "Measuring the effects of unconventional monetary policy on asset prices," Technical Report, National Bureau of Economic Research 2015.

— , "Measuring the effects of Federal Reserve forward guidance and asset purchases on financial markets," Technical Report, National Bureau of Economic Research 2017.

Tella, Sebastian Di and Pablo Kurlat, "Why are Banks Exposed to Monetary Policy?," Technical Report, National Bureau of Economic Research 2017.

Vayanos, Dimitri and Jean-Luc Vila, "A preferred-habitat model of the term structure of interest rates," Technical Report, National Bureau of Economic Research 2009.

Vuolteenaho, Tuomo, "What Drives Firm-Level Stock Returns?," *The Journal of Finance*, 2002, *57* (1), 233–264.

Wang, Yifei, Toni M Whited, Yufeng Wu, and Kairong Xiao, "Bank market power and monetary policy transmission: Evidence from a structural estimation," *Available at SSRN 3049665*, 2018.

Warga, Arthur and Ivo Welch, "Bondholder losses in leveraged buyouts," *The Review of Financial Studies*, 1993, *6* (4), 959–982.

Wright, Jonathan H, "What does monetary policy do to long-term interest rates at the zero lower bound?," *The Economic Journal*, 2012, *122* (564).

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